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Review Article

Land transport network resilience to cascading failures: A systematic literature review of modeling, evaluation, and recovery

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HIGHLIGHTS

- A systematic literature review on resilience to cascading failures in land transport networks was conducted.
- Bibliometric and content analyses were combined to synthesize research progress and trends.
- The main modelling approaches, evaluation metrics, and recovery strategies were identified and compared.
- Critical research limitations and future directions were summarized.

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ABSTRACT

Local failures in land transport networks can escalate into systemic paralysis through cascading effects, severely reducing accessibility and the efficiency of travel. The land transport network encompasses surface passenger and freight transportation systems, including road, rail, metro, public transport and land-based multimodal transport networks with clearly defined transfer connections. This study focuses on the cascading effects of interactions between services and traffic propagating within or across these modes of land transport. To summarise recent advances in modelling, evaluating and recovering from such cascading events, a systematic literature review of peer-reviewed journal articles was conducted. Using the ScienceDirect, Web of Science and Scopus databases, supplemented by cross-reference verification, 180 qualifying studies published between 2015 and 2025 were identified. Then, these research findings were systematically organised using a “modelling-evaluation-recovery” framework. At the modelling stage, load-capacity and coupled map lattice (CML) models account for nearly three-quarters of all reviewed studies, with increasing attention to multilayer interdependencies and behavioural feedback. At the evaluation stage, resilience is increasingly assessed jointly with vulnerability, robustness and reliability, using both topology- and performance-based indicators. At the recovery stage, studies propose interventions such as rerouting, mode-shift management,

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critical component prioritisation and resource allocation to accelerate functional restoration. Despite these advances, a gap between research and practice remains. Contributing factors include insufficient operational data and calibration, overly simplified behavioural and institutional assumptions, and the computational burden of large-scale, high-fidelity simulations. This paper examines how these limitations constrain implementation, proposing actionable solutions such as dynamic behavioural modelling, scenario libraries, data assimilation and real-world validation methods. This review maps advanced methods and metrics and provides guidance on selecting models and designing decision support tools for improving the resilience of land transport networks to cascading failures.

1. Introduction

Land transport networks are fundamental components of integrated transportation systems, playing an indispensable role in societal functioning and economic development. However, their inherent complexity and high interdependence render them highly vulnerable to natural disasters, emergencies, and human-induced disruptions (Mattsson and Jenelius, 2015). In recent years, the increasing frequency of extreme weather events and large-scale emergencies has underscored the risk that localized disruptions can escalate into widespread network failures. For instance, the 2021 torrential downpours in Zhengzhou, China, caused severe road flooding and subway tunnel inundation, leading to bus route suspensions and eventual paralysis of the entire urban transport system, with significant economic losses. Similarly, nationwide strikes in France during 2022 led to successive shutdowns of rail and urban bus services. These localized disturbances rapidly propagated across commuter networks, generating systemic risks and triggering major social disruption. Such incidents highlight the urgent need to enhance the resilience of land transport systems, including their capacity to withstand, adapt to, and recover from cascading failures. Existing studies emphasize that the propagation of risks is influenced by network topology, inter-network coupling mechanisms, node criticality, and system redundancy (Nie et al., 2023; Sun et al., 2024). A systematic review of this research is therefore essential to clarify current progress, identify limitations, and provide theoretical foundations for strengthening transport network resilience and improving emergency response strategies.

In this review, the term “land transport network” refers to the surface mobility system comprising highways, railways, subways and public transport networks, as well as land-based multimodal transport networks that are connected via transfers, shared nodes, interchanges or mode substitutions (Zargiannaki et al., 2024). The methodology clearly defines the scope, boundaries, and exclusions to ensure consistency in model selection and evidence choice.

Cascading failure typically refers to a process in which a localized disturbance propagates through interdependent networks, ultimately leading to systemic collapse. Its defining feature lies in the amplification of a single point of failure through network dependencies, producing a chain reaction (Li et al., 2018). In land transportation systems, this phenomenon is particularly evident. The limited path flexibility of road

networks often prevents effective traffic redistribution following node failures, resulting in widespread congestion (Cao and Cao, 2020; Wang et al., 2024a; Yin et al., 2021; Zhang et al., 2016). Metro systems, constrained by rigid scheduling and serial line configurations, are highly susceptible to complete shutdowns following power or signal failures (Liu et al., 2024a; Ma et al., 2025a; Sun et al., 2022). Similarly, rail networks rely heavily on marshaling yards and dispatch centers, where failures at critical nodes can severely disrupt interregional transport capacity (Jiao et al., 2020). With the rapid expansion of transportation infrastructure, research perspectives have evolved from single-network analyses to coupled and multilayer systems. Examples include robustness analyses of bus-subway networks (Ma et al., 2020a; Sun, 2023) and studies on interdependencies among transport networks, power grids, and road infrastructure (Bin Wee et al., 2023; Xu et al., 2023a). These findings indicate that cascading failures in land transport networks not only cause severe systemic disruptions but also exhibit complex evolutionary patterns arising from cross-network propagation and structural dependencies.

Despite the diversity of subjects and scenarios, research in this field demonstrates strong methodological coherence, typically addressing three central questions. First, how do localized perturbations propagate through network structures and degrade functionality, thereby defining the mechanisms of cascading failure (Chen et al., 2025; Ding et al., 2025; Zhang et al., 2019a)? Second, how can the evolving states of networks during failure processes be effectively quantified and assessed, particularly with respect to vulnerability, robustness, reliability, and resilience (Wang et al., 2021a; Zeng et al., 2025; Zhang and Ng, 2022)? Third, what recovery and control measures can most efficiently allocate resources and restore functionality during large-scale disruptions (Guo et al., 2025a; Song et al., 2025)? These questions are typically examined within a “modeling-evaluation-recovery” framework. The modeling stage focuses on the load-capacity model, CML models, and their enhanced variants to reveal the mechanisms of failure propagation and interdependence. The evaluation stage applies analytical tools such as topological indicators, centrality measures, and propagation thresholds to monitor dynamic changes in network performance. Finally, the recovery phase involves emergency and operational interventions, as well as governance measures. These include redirection of routes, reconstruction of paths, formulation of policies,

prioritisation of critical nodes, and optimised allocation of resources. Together, these three stages form an integrated paradigm combining mechanism analysis, system evaluation, and governance intervention, which together establish the core research framework for cascading failures in land transport networks.

The capacity to recover from cascading failures, or resilience, is crucial for improving the reliability and normal operation of land transport systems. Building upon this research framework, the present paper systematically reviews the resilience of land transport networks to cascading failures through the lens of the “modeling-evaluation-recovery” process. Specifically, it aims to: (1) comprehensively compare dominant modeling approaches, clarify the application boundaries of the load-capacity and CML models, and review their evolution in simulating cascading dynamics for resilience analysis; (2) consolidate resilience evaluation methods and metrics, emphasizing pathways for identifying critical segments and influencing factors; (3) investigate the variety of attack scenario design, failure modes, and recovery strategies reported across studies; (4) pinpoint existing research limitations and propose future research directions.

Fundamental research in complex network science established structural principles and cascading mechanisms that were later adopted in transportation studies. The “small-world” and “scale-free” network structures proposed by Watts and Strogatz (1998) and Barabási and Albert (1999) provided the theoretical basis for many abstract network models. Albert et al. (2000) and Newman (2003) comprehensively elucidated the robustness and functional characteristics of complex networks in the event of failure or attack. Watts (2002) categorised threshold-driven global cascading phenomena; Motter and Lai (2002) modelled load redistribution cascades; and Boccaletti et al. (2006) catalogued core dynamical mechanisms widely used in cascade modelling. Buldyrev et al. (2010) further revealed how interdependencies can amplify the effects of cascades across coupled layers. These landmark studies are cited in order to define the recurring mechanisms and terminology of transportation cascade failure models rather than to extend the systematic sample beyond the review period.

Recent reviews and comprehensive studies have built upon this foundation to summarise transportation network resilience from complementary perspectives. These studies have covered topics such as the resilience assessment and enhancement of integrated urban transportation systems (Yang et al., 2025a; Yussif et al., 2025); multi-modal urban transportation resilience (Chen et al., 2026); interdependency mechanisms (Li et al., 2025c); subway system resilience under external disturbances (Bai et al., 2025); road transport infrastructure vulnerability and resilience (Bashir et al., 2025); resilience to natural disasters and uncertainty (Kibar et al., 2025); and AI-enabled safety and resilience research (He et al., 2025; Liu et al., 2026). While these reviews cover various disruption types and resilience concepts, they generally treat cascading failures as just one type of disruption. This results in a lack of cascade-oriented guidance regarding propagation model selection, metric integration across degradation and recovery phases, and the

linkage between modelling outputs and operational recovery levers.

To address this gap, this study focuses on cascading failures and makes three contributions. Firstly, it systematically integrates mainstream propagation models for highway, rail, metro, public transit and multimodal networks, clarifying application boundaries and selection criteria. Secondly, it clarifies how vulnerability, robustness, reliability and resilience metrics are integrated in actual research, as well as the pathways linking these metrics to modelling outputs and recovery decisions. Thirdly, it summarises operational, practice-based bridging pathways, emphasising calibration, validation, scenario libraries and reproducible outcomes, in order to bridge the gap between modelling and operations. Table 1 illustrates the positioning of this review relative to recent related research.

The remainder of this paper is organized as follows. Section 2 describes the research methodology adopted for the literature review. Section 3 examines the principles and limitations of mainstream modelling approaches. Sections 4 and 5 analyze the evaluation methods and recovery strategies, respectively. Section 6 discusses research gaps and outlines future directions, and Section 7 concludes the paper.

2. Methodology of literature review

2.1. Literature search methods and research distribution

To systematically examine the research progress and challenges associated with cascading failures in land transport networks, this study adopted a rigorous literature collection and screening procedure. As illustrated in Fig. 1, the research process combined database keyword searches, core literature tracking, and multi-stage screening. In the preparatory stage, both bibliometric analysis and content review methods were applied. A set of keywords and their combinations guided the search, including “transportation network”, “cascading failure”, “failure propagation”, “vulnerability”, “robustness”, “reliability”, “resilience”, “identification of critical nodes”, “influencing factors”, “attack patterns”, and “recovery strategy”. Searches were conducted across three major academic databases: ScienceDirect, Web of Science, and Scopus.

In this review, land transport networks is defined as surface transport networks that consist of nodes and links. These networks are characterised by graph structures that incorporate operational status and performance metrics. These networks include road, rail, metro, public transport and land-based multimodal transport networks that operate synergistically through transfers, shared nodes or connection points and mode substitution. Our focus is on cascading failures propagated through functional degradation mechanisms, such as traffic redistribution, capacity overload, cascading delays and transfer spillover effects, as these mechanisms and their corresponding recovery measures are critical to transportation operations.

Table 1 – A comparison of this review with the latest review on transportation resilience research.

Review	Research subjects	Focus	Cascading failure addressed	Contribution
Yang et al. (2025b)	Urban multimodal transportation network	Resilience assessment and enhancement frameworks	Treated as one disruption type	It clarifies the concept of urban integrated transportation network resilience and explores evaluation metrics, assessment methodologies, and optimization measures for enhancement.
Chen et al. (2026)	The multi-modal urban transportation network	Modelling, evaluation, and optimization of multimodal resilience	Partially, via intermodal dependencies	Initiates a thorough investigation within the framework of “network modeling resilience evaluation resilience optimization”, with particular attention to emerging modes such as shared mobility and urban air mobility.
Li et al. (2025c)	Interdependent transport networks	Cross-system coupling and resilience evaluation	Partial, via dependency propagation	Provides a thorough examination of the literature on interdependency and resilience in transportation. Systems.
Bai et al. (2025)	Metro system	Indicator design and recovery strategies	No	Explores methods for enhancing metro system resilience across structural, operational and monitoring dimensions.
Bashir et al. (2025)	Road network	Vulnerability, recovery trends, bibliometric mapping	No	Provides an extensive literature review of scientific articles in the field of vulnerability and resilience of transportation road networks.
Kibar et al. (2025)	Road network; rail network; air network	Resilience definition and metrics under natural hazards	No	Defines “transportation systems resilience”; derives the necessary resilience parameters for different transportation systems.
Liu et al. (2026)	Traffic safety	AI-enabled prediction and recovery decision support	No	Integrates fragmented findings into a lifecycle perspective spanning accident prevention, accident prediction, accident response and recovery.
This study	Land transport network	Modelling-evaluation-recovery integration	Yes	A systematic literature review on resilience to cascading failures in land transport networks was conducted.

To avoid ambiguity, exclude non-transport ground infrastructure networks is explicitly excluded, such as oil and gas pipelines, as well as other utility pipeline networks. This is because their propagation dynamics and operational control mechanisms differ fundamentally from the mobility and service delivery characteristics of transportation systems. Power grids and communication networks are also excluded as primary subjects, as while these systems may exhibit coupling with transportation networks, this study focuses on cascade propagation within transportation networks rather than cross-sectoral infrastructure cascade effects. Furthermore, aviation and maritime networks fall outside the scope of this study as they do not constitute land-based

transportation and operate under distinct operational units and cascade mechanisms. Finally, unless supply chain and logistics networks are explicitly modelled as land transport service networks exhibiting operational status and mobility performance cascade degradation, networks at the enterprise or commodity flow level will not be systematically covered.

The period from 2015 to 2025 is selected as the scope of our research because the literature on transport-oriented cascading failures that we identified is highly concentrated within this decade. This timeframe also reflects the evolution of methodologies, shifting from single-layer analyses focused solely on topology, to data-driven, multi-layer modelling and operation-aware modelling, with an increasing emphasis on

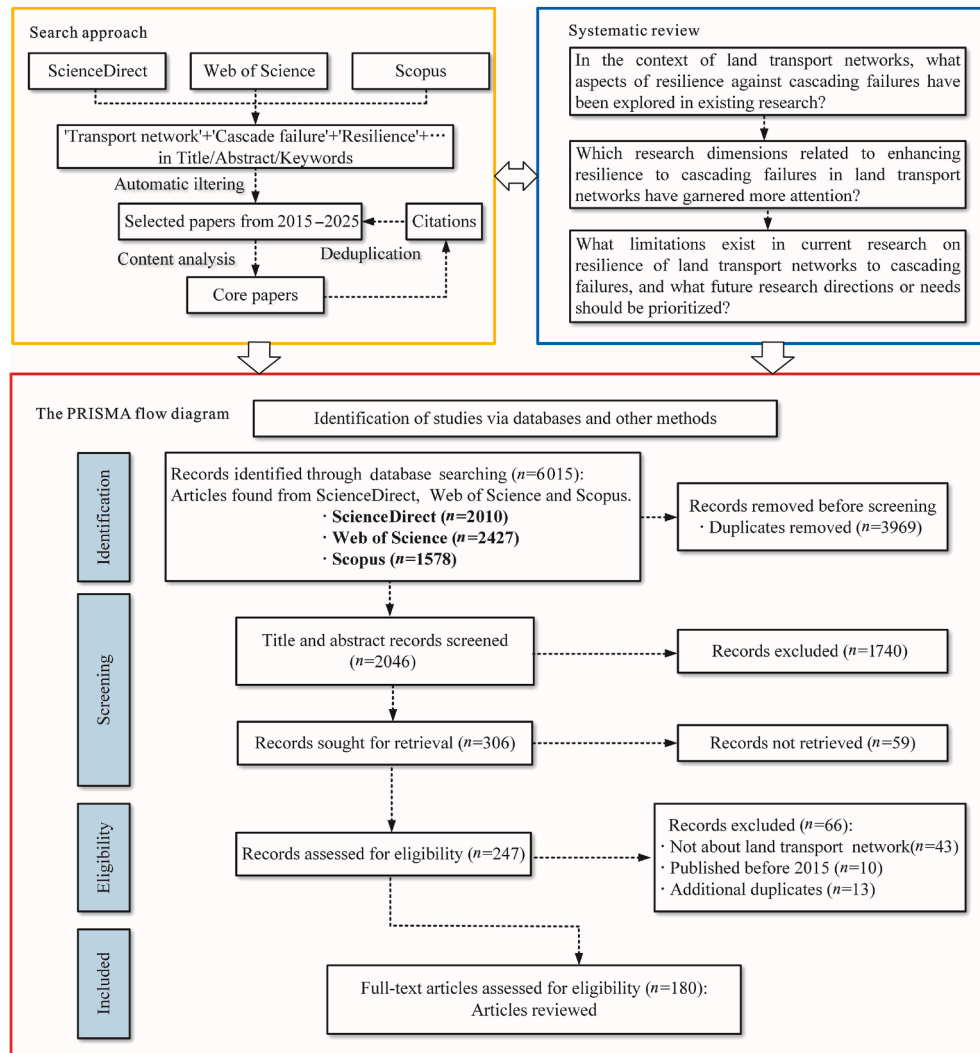


Fig. 1 – Primary research approach and steps.

behavioural patterns, recovery decisions and validation mechanisms. Pioneering research from before 2015 is cited in the introduction to establish the conceptual foundations of network architecture and cascade mechanisms. To ensure transparency and reproducibility, systematic sampling and quantitative distribution are confined to the period from 2015 to 2025. Cross-database verification and comparison against recent reviews minimise the risk of omission.

To enhance the completeness of this study and clarify its positioning relative to recent reviews, the initial literature collection by cross-referencing recent reviews on transportation network resilience systems is validated. Coverage by cross-referencing the bibliographies of seminal papers was further confirmed. This approach helped to identify domain-specific studies on cascading propagation, evolution and recovery that keyword searches alone might have overlooked.

The initial retrieval yielded several thousand studies, from which 180 journal articles published between 2015 and 2025 were selected as the primary data source. The collected literature was analyzed around three interrelated themes, namely modeling, evaluation, and recovery, which together form the

mainstream research paradigm for cascading failures. Fig. 2 presents the distribution of the selected studies by publication year and transport network type. Post-2015 literature focused on data-driven, multi-level and actionable cascading modelling, which aligns with the objectives of this review. This definition aims to ensure the reproducibility of sample statistics. Although foundational studies prior to 2015 were cited as conceptual references, they were excluded from annual distribution statistics and quantitative summaries.

Since 2018, research interest in cascading failures in land transport networks has grown significantly. Metro, public transport, and road networks have attracted the most attention, accounting for 80, 39, and 32 studies, respectively. Because modeling, evaluation, and resilience recovery are often addressed within the same study, separate statistics for each category were not compiled. Table 2 lists the ten journals with the highest publication volumes in this field. The majority of contributions appear in the domains of transportation engineering and system safety. Notably, Reliability Engineering & System Safety and Physica A: Statistical Mechanics and its Applications ranked first and

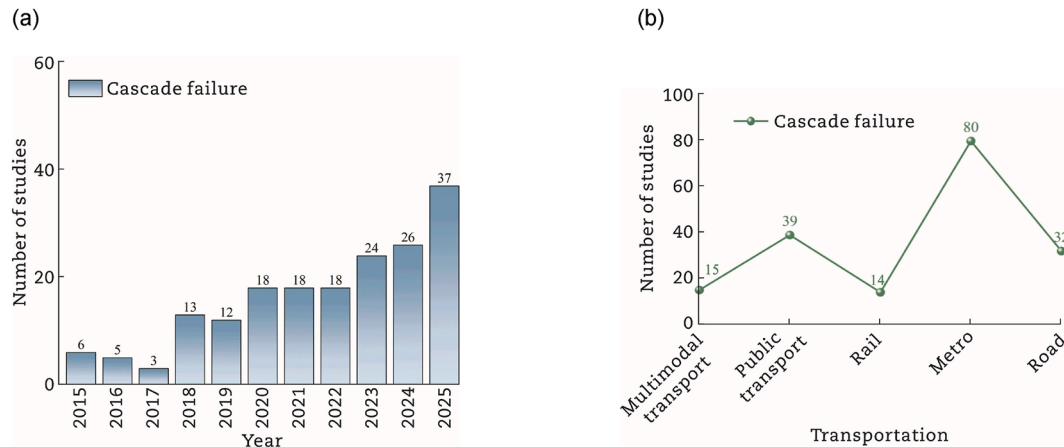


Fig. 2 – Distribution of relevant studies. (a) Publication year. (b) Transportation network type.

Table 2 – Top 10 journals ranked by publication volume in the related field.

Rank	Journal title	Focus	Number of papers
1	Reliability engineering & system safety	Quantifying the probabilistic risk and resilience of transport systems.	35
2	Physica A: Statistical mechanics and its applications	The universal dynamics of cascades, as explained by complex network theory.	30
3	Transport research Part D: Transport and environment	Resilience to climate-induced disruptions and their cascading effects.	10
4	Journal of advanced transportation	Models of network performance degradation based on simulation and algorithms.	10
5	IEEE access	Computational frameworks for modelling resilience and cascading failures.	7
6	IEEE Transactions on intelligent transport systems	Real-time prediction and mitigation of cascading failures.	7
7	Transport research Part C: Emerging Technologies	Proactive resilience and adaptive control.	6
8	Transport research Part A: Policy and practice	Policy and strategic planning for enhancing network resilience.	5
9	Sustainable cities and Society	Inter-system cascades and sustainability, urban resilience.	5
10	Transportation research record	Empirical case studies and applied strategies for infrastructure resilience.	4

second, publishing 35 and 30 related papers, respectively. The scope of this review is limited to major land transport networks including road, rail, metro, and highway systems, while excluding analyses of individual lines or vehicles.

2.2. Keyword feature analysis

This study prioritized keyword feature analysis as a key bibliometric approach to intuitively identify research hotspots in land transport network resilience to cascading failures, as indicated by keyword frequency. Keywords extracted from the three databases were aggregated to generate the word cloud shown in Fig. 3.

Fig. 3 shows that “cascading failure”, “resilience”, and “vulnerability” appear with the highest frequencies, indicating that these represent the core research themes in the field. Keywords such as “transportation network”, “robustness”, “deliberate attack”, “random attack”, “recovery strategy”, “critical nodes”, “complex systems”, “influencing factors” and “failure propagation” also occur frequently,



Fig. 3 – Keywords in the three databases.

reflecting the field's emphasis on various failure types, the identification of key components and factors, and recovery methods. Furthermore, terms such as “infrastructure networks”, “disaster resilience”, and “systemic risk” appear with notable frequency, underscoring the interdisciplinary and practical orientation of this research domain.

To further explore the semantic associations among keywords, CiteSpace was employed to perform keyword co-occurrence and clustering analyses (Cheng et al., 2023; Ji et al., 2023). The results are visualized in Figs. 4 and 5.

As shown in Fig. 4, the keyword co-occurrence network identifies “cascading failure” and “resilience” as the core semantic cluster. This pattern reflects research grounded in complex network theory to enhance resilience against cascading failures. Nodes such as “vulnerability”, “robustness”, and “complex networks” extend the network's semantic landscape, delineating key relationships and research hotspots. In addition, Fig. 5 shows that the clustering map anchors #0 cascading failure as the central cluster, with #2 complex network and #4 complex network theory supporting complex network methodologies, and #3 reliability indexes and #5 social vulnerability expanding the analytical dimensions of research. Core clusters form a tightly interconnected network through co-occurrence relationships. Further refinement through clustering analysis reveals subthemes encompassing theoretical foundations, methodological tools, and application scenarios.

This review also used CiteSpace to analyze the temporal evolution of keywords, as illustrated in Figs. 6 and 7. Fig. 6 shows that “cascading failures” has remained a dominant topic from 2015 to 2025. Keywords such as “interdependent networks” and “complex networks” gained prominence between 2016 and 2018, while “road networks” emerged as a focal theme in 2021. More recently, term like “power system protection” began to appear in 2024–2025, indicating a shift toward cross-infrastructure research.

From a temporal perspective, the theme of cascading failures has remained a persistent research focus, while related subthemes such as robustness and resilience analysis have evolved continuously, as illustrated in Fig. 7. Clusters #3 reliability metrics and #4 complex network theory reflect an

expansion in the scope of evaluation and methodological advancements, respectively. Late-emerging clusters such as #7 complex systems and #8 multilayer networks demonstrate a growing research interest in the deep structure and complexity of interdependent transport systems.

2.3. Core research institutions and authors

To identify the leading academic contributors and collaboration networks in land transport network resilience to cascading failure, CiteSpace was also used to visualize the distribution of research institutions and core authors, as shown in Fig. 8.

As shown in Fig. 8(a), domestic institutions such as Beijing Jiaotong University, Chang'an University, Southeast University, and Tongji University are highly prominent, reflecting their sustained contributions and strong research capacity in this field. Similarly, internationally renowned institutions including State University System of Florida, Arizona State University, and Georgia Institute of Technology also stand out, underscoring extensive global academic participation. The dense interconnections among these institutions, both domestically and internationally, indicate an increasingly collaborative landscape.

Regarding core authors, Fig. 8(b) identifies scholars such as Wu Jianjun, Chen Hong, and Wang Jianwei as leading figures in domestic research, each of whom has developed extensive academic networks that form influential research clusters. Internationally, scholars such as Mohamed Ezzeldin, Auroop R. Ganguly, and Michael M. Danziger are recognized as key contributors. Collaborations between domestic and international researchers highlight the growing global integration of the research field.

3. Decoding network resilience: modeling approaches for cascading failure dynamics

Cascading failure models are fundamental analytical tools for examining the vulnerability and resilience of transportation networks. These models aim to reveal how failures propagate within complex systems and how such propagation affects overall network stability. To capture these mechanisms, scholars have developed several modeling approaches, including load-capacity, CML, disaster propagation dynamics, OPA, sandpile, binary influence, and CASCADE models. Among these, the load-capacity and CML models have been most widely applied to land transport systems and have emerged as mainstream approaches. In the 180 articles examined, around 43% used the load-capacity framework and around 30% used CML-type formulas. This confirms their dominance as the two main models for analysing transportation cascades. A comparative overview of these two dominant models is provided in Table 3. Beyond these, other models contribute complementary insights: the disaster propagation dynamics model characterizes transmission through diffusion dynamics (Ding et al., 2024; Lu et al., 2024); the OPA model captures the interaction between load and failure over long-term evolution (Xing et al., 2018); the

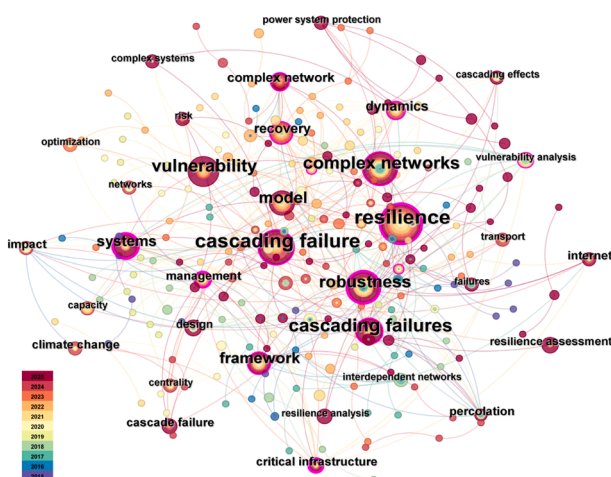


Fig. 4 – Keyword co-occurrence analysis.

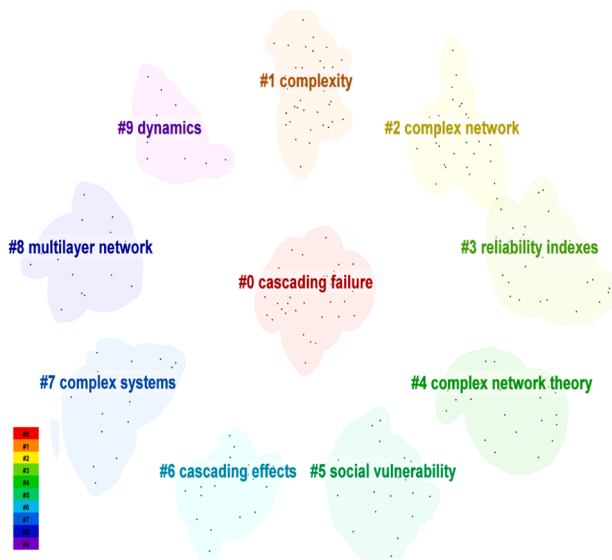


Fig. 5 – Keyword clustering analysis.

Keywords	Year	Strength	Begin	End	2015–2025
community structure	2015	1.2	2015	2016	
interdependent networks	2016	2.66	2016	2018	
fragility	2016	1.77	2016	2017	
extreme weather	2016	1.58	2016	2020	
failures	2016	1.26	2016	2018	
complex networks	2016	2.38	2017	2018	
scale	2018	1.27	2018	2018	
reliability	2018	1.27	2018	2018	
methodology	2020	1.22	2020	2020	
water distribution networks	2020	1.22	2020	2020	
topology	2020	1.22	2020	2020	
complex network theory	2020	1.19	2020	2022	
model	2016	2.34	2021	2023	
road network	2021	1.78	2021	2021	
recovery	2018	1.35	2021	2025	
safety	2021	1.18	2021	2021	
supply chain	2021	1.18	2021	2021	
network topology	2021	1.18	2021	2021	
links	2016	1.66	2022	2022	
system	2023	1.84	2023	2023	
optimization	2020	1.67	2023	2023	
climate change	2016	1.33	2023	2025	
cascading failure	2015	1.9	2024	2025	
power system protection	2024	1.68	2024	2025	
transport	2021	1.47	2024	2025	

Fig. 6 – Keyword bursts analysis.

sandpile model emphasizes cascading effects at critical thresholds, the binary influence model reveals stochastic propagation patterns through binary state transitions; and the CASCADE model highlights cross-system topological coupling. Collectively, these models enrich the theoretical understanding of cascading failures but remain limited in their direct applicability to real-world transportation systems.

3.1. Current status and development of load-capacity model research

The load-capacity model, a foundational framework for studying cascading failures in complex networks, typically consists of three core components: initial load definition, capacity determination, and load redistribution mechanisms. Accordingly, three methodological issues must be addressed.

- (1) How should metrics for the initial load be defined appropriately?
- (2) How should the maximum load capacities of nodes and edges be determined?
- (3) How should load be redistributed across the network during localized failures to realistically represent propagation and evolution processes?

Within this framework, cascading failures in land transport networks generally arise from mismatches between load and capacity. When critical nodes, such as intersections, subway transfer stations, or railway marshaling yards, or edges like roads, tracks, or rail segments, exceed their design capacities, excess traffic is redistributed to other components of the system. This process can lead to secondary overloads and trigger chain reactions of failure. In practical applications, load is typically defined using measured or statistical data such as passenger volume, vehicle flow, or freight throughput, reflecting the actual usage intensity of a facility. Conversely, capacity is often quantified based on road classification, station design limits, traffic control constraints, or maximum throughput levels. To account for uncertainty, capacities are often adjusted to reflect variations between peak and off-peak periods, weather disturbances, or unexpected incidents. Finally, post-failure load redistribution mechanisms play a central role in propagation analysis. A widely adopted approach is the path-selection model based on Wardrop's equilibrium theory, which assumes that travelers choose routes that minimize travel costs until a network-wide equilibrium is achieved.

In recent years, scholars have continuously refined load-capacity models to extend their applicability across various cascading failure scenarios. Within the context of land transport networks, these developments can be summarized as follows.

- (1) Load representation. Load may be assigned to nodes, edges, or both simultaneously (Wang and Tian, 2020).
- (2) Initial load definition. Multiple approaches have been adopted, including definitions based on shortest paths (Wang et al., 2024b), degree functions (Wang and Tian, 2020), path flow capacities (Guo et al., 2025b), or actual traffic volumes (Zhang et al., 2016). The choice of metric typically depends on the specific application scenario.
- (3) Capacity–load relationships. These may be linear, nonlinear, or independent. In most studies, capacity reflects road or station design constraints, often resulting in nonlinear relationships with initial load (Chen et al., 2024a; Jin et al., 2022a; Ma et al., 2020a).

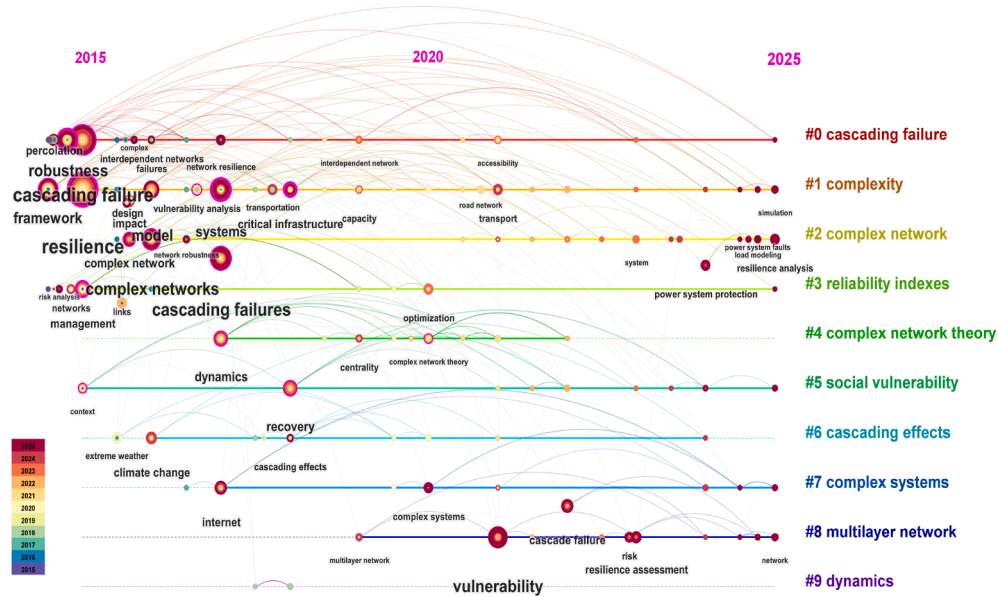


Fig. 7 – Keyword cluster timeline view.

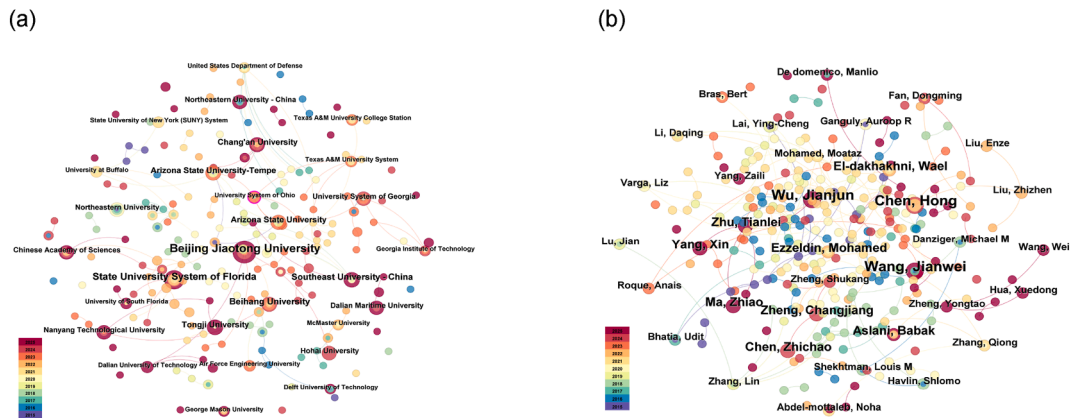


Fig. 8 – The distribution of research institutions and core authors. (a) Research institutions. (b) Core authors.

- (4) Load redistribution strategies. Redistribution following node failure has been modeled through several mechanisms: average distribution (Jin et al., 2022a; Yin and Song, 2023), random distribution (Du et al., 2025), locally optimal distribution (Jia et al., 2020), or globally optimized distributions (Guo et al., 2020a). Advanced variants apply weighted allocations based on traffic pressure (Yin et al., 2021), capacity margins (Shen et al., 2022), intermediary centrality (Jung et al., 2020), freight costs (Zeng et al., 2025), or fuzzy decision-making techniques (Du et al., 2025).
- (5) Node state classification. While most studies adopt a binary classification of normal versus failed states, some introduce additional states such as overload (Lin et al., 2025; Wang and Tian, 2020), pause (Li et al., 2021), or congestion (Ding et al., 2025).

Overall, these refinements have significantly strengthened the explanatory and predictive power of load-capacity models, enabling them to capture a broader spectrum of cascading failure dynamics in land transport networks.

3.2. Current status and development of CML model research

Although the load-capacity model effectively describes the relationship between node load and capacity, it has limited ability to capture the intricate coupling mechanisms among nodes and the nonlinear dynamics underlying cascading failures. To address these shortcomings, many scholars have turned to the CML model, which integrates network topology and real-time node states to analyze failure propagation. Existing studies can be broadly classified into two main research streams.

Table 3 – Comparison of the load-capacity model and the CML model.

Model name	Principle	Advantage	Disadvantage	Application
Load-capacity model	Nodes fail when the load exceeds capacity, redistributing load to adjacent nodes and potentially triggering cascades.	Links load with capacity; effective for vulnerability evaluation	Idealized distribution; overlooks adaptive dynamics	Road network (Chen et al., 2024a); metro network (Ding et al., 2025; Wang and Tian, 2020); public transport network (Hu et al., 2025; Li et al., 2021; Ma et al., 2020a; Wang et al., 2025); multimodal transport network (Zeng et al., 2025).
CML model	Node state depends on the node itself and its neighbors; capturing nonlinear spatiotemporal dynamics.	Models coupling and nonlinear propagation	Computationally intensive; parameter-sensitive	Road network (Hassan et al., 2022); metro network (Li et al., 2024a; Ma et al., 2023a; Wu et al., 2021a; Zhang et al., 2021a); rail network (Chen et al., 2024b); public transport network (Chen et al., 2025; Li et al., 2024b).

- (1) Analyses based on the traditional CML model.
- (2) Analyses using improved CML models that incorporate additional factors.

The traditional CML model has primarily been applied to urban rail transit networks (Li et al., 2024a; Wu et al., 2021a; Xiong and Yao, 2020) and multilayer public transport systems (Li et al., 2024b), where cascading failures are generally triggered by passenger flow dynamics. Findings consistently indicate that stronger coupling intensity and larger perturbations significantly increase the likelihood of systemic failure. However, most of these studies incorporate only passenger flow analysis into the model, overlooking broader structural, operational, and environmental dimensions.

To overcome these limitations, scholars have extended the traditional framework by incorporating network topology (Ma et al., 2023a; Xu et al., 2022; Zhang et al., 2015a), external disturbances (Sun, 2023; Wang et al., 2021b), and node resilience attributes (Lu et al., 2022; Zhang et al., 2024a). These refinements provide a more realistic representation of cascading dynamics in land transport systems. For instance, Shen et al. (2021) developed a bidirectional CML model for the Nanjing metro network, accounting for two-way traffic flows to better reflect operational conditions. Their findings showed that metro systems are considerably more vulnerable to targeted attacks than to random failures, and that global failures are more likely to originate from maximum-intensity nodes rather than maximum-degree nodes. Similarly, Zhang et al. (2023) proposed an improved CML model to simulate cross-level cascading interactions between bus and metro networks, integrating both job dependencies and geographical interdependencies into the evolution of node states. Their analysis demonstrated that neglecting such interdependencies results in a significant overestimation of metro failures and underestimation of bus disruptions. Ye and Luo (2021) further introduced a graph attention network-based CML model, using Shanghai metro operational data to capture passenger behavior and simulate cascading evolution within a deep

learning framework. The results revealed that the Shanghai subway network remains robust against random failures but highly vulnerable to intentional disturbances. Furthermore, the cascade failure rate followed an approximately normal distribution over time, indicating a steady-state convergence pattern under recurring perturbations.

In summary, the continuous evolution of CML models demonstrates a clear trajectory toward the integration of structural, behavioral, and data-driven elements. These advancements enhance the explanatory strength of the model, enabling a deeper comprehension of the nonlinear dynamics underlying cascading failures in land transport networks.

3.3. Emerging modeling methods and development trends

In recent years, scholars have progressively advanced modeling techniques to better capture the operational mechanisms of real-world transport systems, leading to several innovative methodological frameworks. Duan et al. (2023) proposed a two-layer cascading failure model to examine route-selection behavior during congestion evolution. The lower-layer model addresses travelers' route choices under the trade-off between user equilibrium and system optimality, highlighting behavioral influences in cascading processes and moving beyond traditional load redistribution models. Yang et al. (2023) introduced a rank-order centroid (ROC)-based Cross-Impact Analysis and Interpretive Structural Modeling (CIA-ISM) framework to investigate cascading failures in subway networks exposed to extreme rainfall conditions. This scenario-driven approach emphasizes interdependencies among critical events, offering clearer insights into coupling relationships and enhancing system decoupling efficiency. Lu et al. (2024) developed an improved DST model incorporating time delays, origin-destination (OD) demand variations, and spatiotemporal heterogeneity of passenger flows to reflect real operational dynamics. Shen et al. (2024) designed a

Table 4 – Comparison of emerging modeling methods.

Model name	Feature	Application scenario
Two-layer cascading failure model (Duan et al., 2023)	Balances route choice between equity and optimality, incorporating travel behavior.	Congestion simulation, travel behavior modeling
CIA-ISM model ROC-based centrality (Yang et al., 2023)	Analyzes cross-impacts among key events, clarifying coupling relationships.	Cascading risk identification in metro networks
Improved DST model (Lu et al., 2024)	Considers delays, origin-destination demand variations, and spatiotemporal heterogeneity.	Multimodal cascading analysis
Cascading overload model (Shen et al., 2024)	Maps station flow to layered networks with dynamic capacity-flow updates.	Metro facility failure modeling
Biased random walk model (Song et al., 2025)	Incorporates centrality and degree distributions, simulating overload propagation.	Metro load fluctuation analysis
Pass-passenger assignment model (Guo et al., 2025b)	Applies Tsallis entropy to balance loads and redundancy.	Resilience assessment of coupled bus-metro systems
SEFR model (Kays et al., 2025)	Combines hydrological data with multi-layer network topology.	Flood-induced cascading in road networks

cascading overload model for subway station facilities, mapping both facilities and passenger flows onto a hierarchical directed network dynamically updating through impedance functions and mutual flow redistribution. Song et al. (2025) proposed a biased random walk model that integrates power-law distributions of betweenness centrality and node degree to analyze metro failures arising from extreme load fluctuations. Guo et al. (2025b) introduced a pass-passenger assignment model based on path flow capacity and Tsallis entropy, which leverages intermediate centrality and structural hole theory to refine initial flow allocation and enhance resilience assessment. Finally, Kays et al. (2025) developed a susceptible-exposed-flooded-recovered (SEFR) model to simulate flood-induced cascading failures in road networks. This approach integrates multi-layer network topology with hydrological data, enabling accurate capture of dynamic propagation patterns under extreme environmental stress. A comparative overview of these methods is provided in Table 4. To further clarify their mathematical underpinnings, Table 5 summarizes the core formulations, parameters, and distinctive features of representative cascading failure models.

Taken together, these innovative approaches reveal three key development trends.

- (1) From topology-driven to behavior-driven modeling. New approaches incorporate passenger flow patterns and risk perception to more accurately mirror traveler behavior during cascading processes.
- (2) From static analysis to temporal dynamics. By integrating demand variation, time delays, and spatiotemporal heterogeneity, models capture the evolving characteristics of cascading failures and adapt better to real-world operations.
- (3) From isolated failure analysis to failure-recovery coupling. Emerging frameworks integrate critical node interactions, environmental exposures, and recovery mechanisms, enabling more comprehensive assessments of network vulnerability and resilience.

These advances reflect a growing effort to bridge theoretical modeling with real-world transport operations. Building

on this progress, the present study further synthesizes the distinct modeling characteristics of cascading failures across different types of land transport networks, as illustrated in Fig. 9.

3.4. Model applicability and selection guidelines across land transport network types

The applicability of cascade failure models varies by transport network type, as the two main models have different propagation logics. The load-capacity model describes cascading phenomena as overload and redistribution in relation to capacity constraints. It is most effective in scenarios where load, capacity and failure states can be determined through operational measurements, such as passenger and vehicle flow rates, capacity based on schedules and facility throughput. CML-based models, on the other hand, describe non-linear state evolution and amplification effects through coupled dynamics. These models apply to cascades driven by interacting time-varying congestion and delay states and feedback between interconnected nodes. In practice, these models are often implemented through traffic-specific instantiation and hybrid extensions, such as flow-based traffic models for roads, timetable-aware capacity constraints for railways, and passenger flow redistribution dynamics for subways.

Given this context, model selection should be differentiated based on the most commonly studied network types. Road networks are link-centric and governed by continuous traffic flow dynamics, where spillover effects and path re-selection dominate propagation. Rail networks are constrained by track segments, marshalling yards and operational rules. Metro networks are usually station-centric and schedule-constrained, exhibiting strong passenger redistribution and transfer coupling characteristics. Public transport networks focus on routes and stops and often feature elastic demand, transfer spillover effects and shared corridors. Multimodal transport networks involve intermodal transfers and mode substitution. Therefore, when selecting a model, the following should be considered: load and capacity definitions, dominant propagation mechanisms, modelling granularity, decision-making leverage and calibration feasibility with operational

Table 5 – Mathematical formulation and characteristics of partial cascading failure models.

Modeling method	Core formula	Variable description	Modeling feature	Applicable network type	Representative literature
Load-capacity model	$F_i(t) = \begin{cases} 1 & \text{if } L_i(t) > C_i \\ 0 & \text{otherwise} \end{cases}$ $L_j(t+1) = L_j(t) + \sum_{i \in F(t)} \frac{L_i(t) A_{ij}}{\sum_k A_{ik}}$	$L_i(t)$: load of node i at time t C_i : capacity of node i $F(t)$: set of failed nodes at time t A_{ij} : connection relationship between nodes i and j	Failure occurs when load exceeds capacity; load is redistributed according to adjacency relationships.	Road network, metro network	Wang and Tian (2020)
Coupled map lattices model	$x_i(t+1) = (1 - \epsilon)f(x_i(t)) + \frac{\epsilon}{ I(i) } \sum_{j \in I(i)} f(x_j(t))$ $f(x) = \mu x(1 - x)$	$x_i(t)$: State of node i at time t ϵ : coupling strength $I(i)$: neighbor set of node i μ : nonlinear parameter	Captures nonlinear coupling and chaotic behavior; suitable for dynamic propagation simulation.	Metro network, bus-metro network	Zhang et al. (2021a)
Improved CML model (bidirectional passenger flow)	$x_i^{\text{in/out}}(t+1) = (1 - \epsilon)f(x_i^{\text{in/out}}(t)) + \frac{\epsilon}{k_i^{\text{in}}} \sum_j A_{ji} f(x_j^{\text{out/in}}(t))$	$x_i^{\text{in/out}}$: passenger flow state of node i for entry/exit k_i^{in} : in-degree of node i A_{ji} : connection from node j to i	Distinguishes between inbound and outbound passenger flows, better aligning with actual operations.	Metro network	Shen et al. (2021)
Path flow capacity-based tsallis entropy model	$P_k = \frac{(1 - (1 - q)\beta T_k)^{\frac{1}{1-q}}}{\sum_k (1 - (1 - q)\beta T_k)^{\frac{1}{1-q}}}$	P_k : probability of path k being selected T_k : travel time of path k q : tsallis entropy parameter β : sensitivity coefficient	Introduces non-extensive entropy theory, balances load and redundancy, improves initial flow allocation rationality.	Bus-metro network	Guo et al. (2025b)
Biased random walk model	$\Pi_{i \rightarrow j} = \frac{k_j^\alpha B_j^\beta}{\sum_{m \in I(i)} k_m^\alpha B_m^\beta}$	$\Pi_{i \rightarrow j}$: transition probability from i to j k_j : degree of node j B_j : betweenness centrality of node j α, β : adjustment parameters	Combines degree and betweenness to simulate load fluctuation propagation.	Metro network	Song et al. (2025)

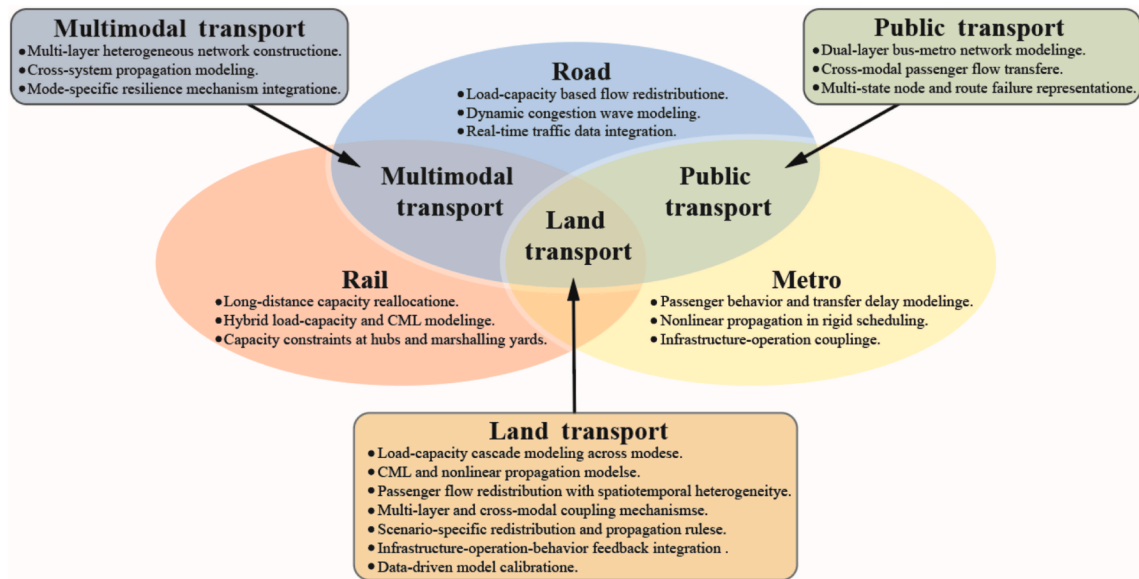


Fig. 9 – Modeling characteristics of cascading failures in different types of land transport networks.

data. Table 6 summarises the correspondences for the most common types of land transport network.

Transport-specific extension and hybrid instantiation methods, such as flow distribution heuristics, random walk propagation and learning-enhanced dynamics, are most effective when anchored to operational units and decision contexts specific to particular network types. In practice, numerous studies adopt a hybrid design approach, retaining a mechanism-based core framework (typically a load capacity or CML model) while incorporating behavioural modules and data-driven calibration mechanisms to improve actual accuracy and decision relevance.

4. Quantifying network resilience: evaluation metrics and impact propagation

Evaluation plays a pivotal role in cascading failure research, serving as the bridge between modeling and recovery. It identifies the evolving states of transportation networks during failure events, based on modeling outcomes, and provides quantitative evidence to guide subsequent recovery and management decisions. A systematic review of evaluation methods and metrics is therefore essential to understanding research progress in this domain. Existing studies generally fall into three major methodological approaches. The first relies on network topology, employing indicators such as vulnerability, robustness, reliability, and resilience to characterize how system performance degrades under perturbations and uncertainty. The second incorporates passenger flow characteristics, examining travel demand distribution, traffic dynamics, and behavioral mechanisms to capture variations in propagation range and speed across temporal and spatial conditions. The third focuses on critical nodes and influencing factors, using threshold analysis and sensitivity testing to reveal failure-triggering and amplification mechanisms. Together, topology

attributes, passenger flow, and critical node identification form the core framework for evaluating cascading failures.

4.1. Evaluation dimensions and methods

Research on cascading failures in land transport networks generally revolves around four primary evaluation dimensions: vulnerability, robustness, reliability, and resilience. Vulnerability emphasizes the structural sensitivity of networks to localized disturbances. It typically employs topological indicators such as degree, path length, and centrality to identify the contribution of critical facilities to overall connectivity (Lu et al., 2022; Ma et al., 2020b; Ye et al., 2025). Robustness highlights network stability under disruptions by incorporating capacity and flow constraints. Methods such as seepage theory and load-capacity models are often used to characterize congestion propagation and functional degradation, illustrating how supply-demand imbalances influence overall stability (He et al., 2021; Hu et al., 2025; Jiang et al., 2024). Reliability evaluates a network's ability to sustain service performance under uncertainty, including demand fluctuations, facility failures, and random traveler behavior. Probabilistic models and Monte Carlo simulations are widely applied to estimate accessibility and delay probabilities (Chen et al., 2024c; Duan et al., 2023; Nie et al., 2023). Resilience extends evaluation perspective to cover system evolution and recovery, considering performance degradation, route alternatives, repair operations, and resource allocation. Time-varying dynamic models are used to quantify performance retention and recovery efficiency (Liu et al., 2022a, 2025; Ma et al., 2025b). Table 7 summarizes representative methods and features across these four dimensions.

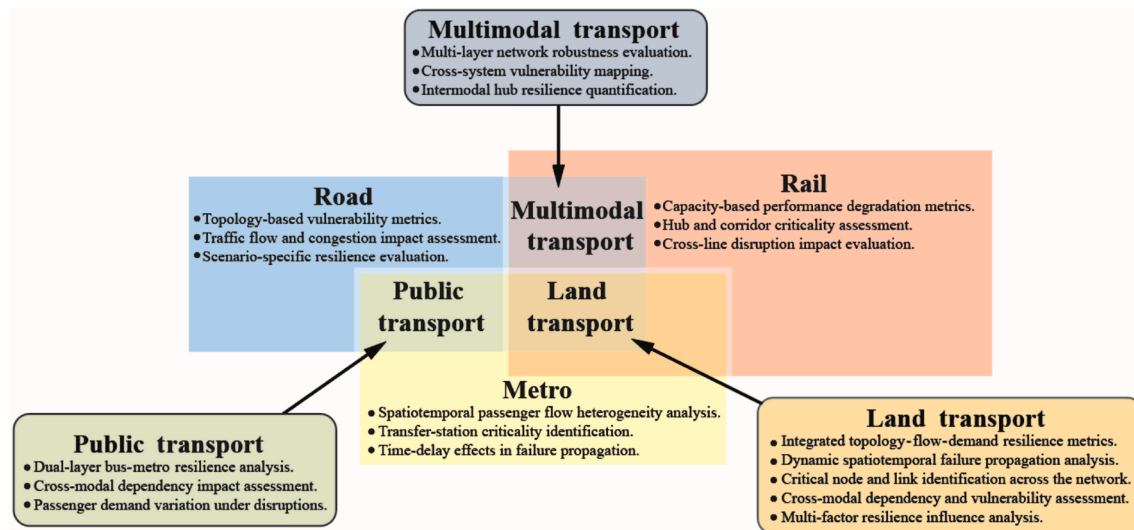
These dimensions are applied differently across network types, as shown in Fig. 10. For example, Zhang et al. (2018) emphasized that most existing studies remain centered on topological efficiency, which reveals vulnerability but fails to

Table 6 – Model applicability of load-capacity and CML models across land transport network types.

Network type	State	Trigger	Model and extension	Metric	Calibration
Road	Link-based; continuous flow; spillback and reroute	Incidents; work zones; cap drop; extreme weather	Load-capacity; CML needs link-states and spillback	Delay and queues; throughput; reliability; signals and ramp; reroute	Counts and speeds; incident logs; OD; control settings
Rail	Segment and yard-based; timetable and resources	Blockage; yard congestion; equipment shortage; knock-on delay	Load-capacity with timetable and resources; CML-like delay-states and dispatch	On-time; delays; service level; reroute and priority; yard capacity	Timetable and dispatch; yard rates; delay records; inventories
Metro	Station-based; pax flow and transfer; schedule	Closure; signal and traction; peak crowding; hub attack	CML with flow; station capacity and dwell; option thresholds	Resilience curve; delay and throughput; reopen sequence; headway and dispatch	OD; headway logs; station cap proxies
Public transport	Route and stop-based; elastic demand; transfers and corridors	Route break; depot fail; bunching; weather	Load-capacity; CML spillover; multilayer	Travel time; completion; efficiency; detours and fleet; timetable options	Ridership; transfer OD; corridor speeds
Multimodal transport	Cross-layer transfers; shared infra; mode substitution	Layer disruption; demand shift; multi-hazard	Hybrid by layer; transfer and mode-choice coupling; data-driven	Accessibility; OD completion; equity; coordinated restoration; information and demand	Transfer penalties; mode-choice; incidents

Table 7 – Comparison of the four evaluation dimensions.

Dimension	Focus	Method	Feature	Related research
Vulnerability	Sensitivity and weaknesses of networks under local disturbances	Topological structure indicators include degree, centrality, shortest path, and connectivity	It is mostly based on complex network theory and static topology analysis, with an emphasis on identifying key nodes and sections	Bell et al. (2017); Candelieri et al. (2019); Chen et al. (2021); Darayi et al. (2017); Dehaghani and Morency (2025); Jiang et al. (2018); Jung et al. (2020); Lin et al. (2024); Liu et al. (2020a); Lu et al. (2022); Ma et al. (2020b); Ma et al. (2019); Wang et al. (2023a); Ye et al. (2025)
Robustness	Network stability and ability to maintain function during disturbances	Seepage theory, load-capacity model, congestion propagation indicators, and traffic supply-demand balance	Focus on dynamic traffic allocation and capacity constraints while considering failure propagation effects	Aparicio et al. (2022); Cao and Cao (2020); Cao et al. (2025); Dong et al. (2020); Fan et al. (2020); Hassan et al. (2022); He et al. (2021); Hu et al. (2025); Jiang et al. (2024); Ma et al. (2025a); Pagani et al. (2019); Wandelt et al. (2021); Wu et al. (2021b)
Reliability	The network's ability to maintain service under uncertainty	Probability theory, stochastic processes, Monte Carlo simulation	Emphasizes accessibility and delay probability in uncertain scenarios	Chen et al. (2024b, 2024c); Duan et al. (2023); Nie et al. (2023); Wu et al. (2021a); Zhang et al. (2019a)
Resilience	The evolution and recovery capacity of networks during the early, middle, and late stages of disturbances	Function retention rate, recovery efficiency, alternative path utilization rate, and emergency repair efficiency	Mostly uses time-varying dynamic models and recovery simulations, incorporating repair strategies, resource allocation, and passenger behavior	Jia et al. (2025); Kays et al. (2024); Liu et al. (2022a, 2022b, 2025); Lu et al. (2025); Ma et al. (2025b); Wang et al. (2023b); Xu et al. (2025); Zhang et al. (2019b, 2024b)

**Fig. 10 – Evaluation characteristics of cascading failure studies in different types of land transport networks.**

adequately capture flow dynamics, behavioral feedback, and multi-network interactions. Zhang et al. (2022a) highlighted that cascading failures are jointly shaped by topological structure, travel demand, traffic distribution, and management strategies.

4.2. Failure propagation evaluation considering passenger flow

Passenger flow is a decisive determinant of cascading failures, influencing both load levels and the localized

disruption propagation. Initially treated as a background variable, passenger flow has increasingly been recognized as a dynamic driving factor in cascading processes. Failures occur when instantaneous passenger loads exceed the designed capacity of specific nodes (Dong et al., 2023; Shen et al., 2020a, 2023; Zhang and Ng, 2022; Zhu et al., 2024). Unlike earlier studies that idealized total load as constant, more recent work acknowledges temporal fluctuations, particularly during peak periods, which exacerbate overload risk and intensify cascading effects. Stations exposed to sustained passenger influx may experience delayed overloads, even after initial emergency measures. A noteworthy finding is that increasing node capacity does not always improve system resilience. Wang et al. (2016a) observed in both road and airport networks that capacity expansion could reduce cascading resilience by introducing nonlinear instabilities.

Studies employing complex network theory and dynamic modeling consistently demonstrate that passenger flow evolution during disruptions is tightly coupled with the topological structure of the transport network (Yin et al., 2022; Zhang et al., 2021a; Zhou et al., 2023). Building upon this, several scholars emphasize incorporating passenger behavioral responses into cascading failure analysis (Lu et al., 2025; Yang et al., 2025a, 2025b; Yin et al., 2022). Passenger flows exhibit strong spatiotemporal heterogeneity: spatially, they vary significantly across stations and lines in different regions (Fan et al., 2020; Guo et al., 2020b; Xiao et al., 2018); temporally, peak-hour conditions cause sharper imbalances in station capacity and transfer resilience (Hu et al., 2025). This heterogeneity results in uneven capacities to accommodate redirected passengers, leading to diverse propagation pathways of cascading failures. To capture these dynamics, some studies have incorporated static passenger characteristics into evaluation frameworks. For example, Sun et al. (2018) proposed a multi-static passenger-flow-weighted network to examine how passenger heterogeneity influences cascading failures. Their results revealed that stations with the highest connectivity were more prone to cascading failures than those with the largest passenger flows. Similarly, Shen et al. (2021) and Zhang et al. (2021a) developed bidirectional network models of metro systems, demonstrating that unidirectional or cross-sectional passenger data fail to adequately reflect real passenger flow dynamics.

In addition to spatial load redistribution, cascading failure analysis must consider temporal propagation factors, such as the duration and interval of failure propagation (Guan and Chen, 2018; Guo et al., 2025a; Lei et al., 2025). In urban rail transit networks, time delays are inherent, as disruptions at one station do not immediately impact adjacent stations due to passenger transfer times. Qian et al. (2015) simulated cascading failures in road networks and found that introducing appropriate time delays can actually mitigate failure propagation. This highlights the importance of modeling delay effects in both analytical evaluation and operational management, since delays substantially affect failure dynamics and outcomes. However, most existing studies treat time delay simplistically, using coarse estimations or assuming that it occurs only during failure

propagation. Recent research underscores that time delays and demand variations must be considered jointly, as propagation flows are inherently dynamic (Gao et al., 2021; Jin et al., 2023; Tak et al., 2018). For instance, Zhang et al. (2022b) noted that during cascading failures, passengers frequently shift to alternative transport modes, altering OD demand patterns and reducing the overall intensity and spatial reach of cascading failures. To quantify this phenomenon, Shen et al. (2020b) proposed a ratio coefficient that measures the proportion of passengers transferring to other modes.

4.3. Identification of critical segments and factors

Effectively preventing cascading failures in land transport networks requires identifying critical nodes and segments that most influence system stability. While many studies address this issue, it is often treated as a secondary component within broader resilience assessment. Only a limited number of works explicitly focus on critical node or segment identification as their primary objective (Barati et al., 2024; Huang et al., 2025; Jin et al., 2022b, 2025; Jing et al., 2020; Li et al., 2025a, 2025b; Ma et al., 2023b; Tian et al., 2021; Wang et al., 2016b, 2024c; Xu et al., 2018; Zhang et al., 2015b; Zhou and Wang, 2017; Zhou et al., 2025). Mainstream methods for identifying critical segments can be categorized into three principal approaches, as illustrated in Fig. 11.

- (1) Static structural evaluation, which uses centrality metrics (e.g., degree, betweenness, closeness, eigenvector) or multi-metric fusion to assess node or link importance within a static topological framework (Tian et al., 2021; Yang et al., 2015; Zhang et al., 2015b; Zhou and Wang, 2017).
- (2) Dynamic evolution analysis, which simulates network disruptions (e.g., deletion or failure) to observe cascading impacts on system performance (Darayi et al., 2017).
- (3) Comprehensive recognition methods, which apply improved algorithms such as PageRank, k-shell, and TOPSIS to integrate both local and contextual attributes (Ma et al., 2023b; Xiao and Ren, 2024).

Beyond single-link assessments, some scholars have investigated combinational vulnerability analysis. For instance, Wang et al. (2016b) proposed a global optimization framework to identify the most critical link combinations within transport networks. Their findings revealed a counterintuitive result: the most vulnerable multi-link sets are not merely the aggregation of individual weak links, nor are they necessarily spatially adjacent. Similarly, Jin et al. (2022b) developed a two-level mixed-integer nonlinear programming model for urban road networks under multiple disruption scenarios. Their results confirmed that critical multi-link failures often involve road segments that are not the most vulnerable in isolation and may even lack direct physical connectivity.

In static structural evaluation, critical segments in land transport networks are typically identified by ranking topological centrality indicators, such as degree centrality (Zeng

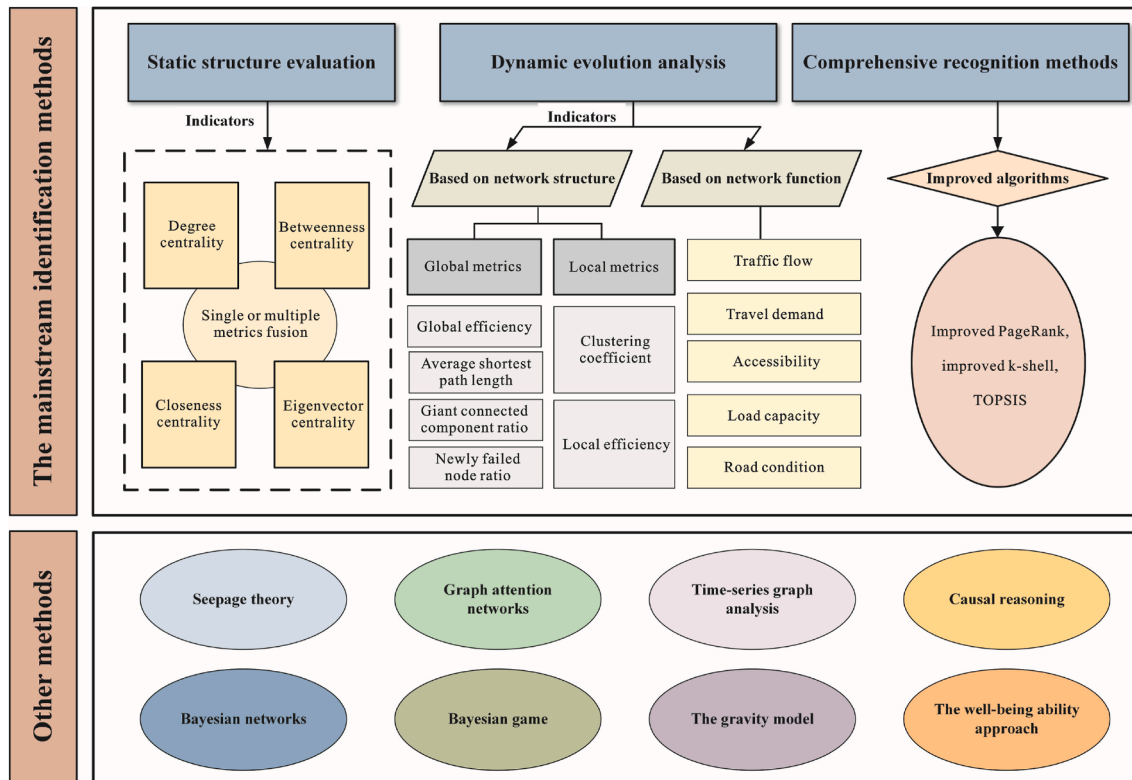


Fig. 11 – Methods for identifying critical stations or sections in existing studies.

et al., 2025), betweenness centrality (Lu, 2018), closeness centrality (Jiang et al., 2018), and eigenvector centrality (Zhang et al., 2015b). While these indicators capture both local and global network properties, they are relatively simplistic and prone to bias, making it difficult to accurately identify critical nodes and links in complex real-world environments. To address this limitation, several studies have adopted multi-indicator fusion strategies to enhance identification accuracy (Dehaghani and Morency, 2025; Hu et al., 2022; Zhang et al., 2015b; Zhang and Ng, 2022). In dynamic evolution analysis, scholars simulate cascading failure processes to evaluate their impacts on overall network functionality. Measurement approaches generally fall into two categories: topology-based and performance-based. Topology-based simulations are advantageous due to their relatively low data requirements. They often replicate abrupt disruptions through random or targeted attacks guided by centrality metrics. Common indicators include global efficiency (Cao and Cao, 2020; Wang et al., 2019), average shortest path length (Yang et al., 2015), maximum connected subgraph ratio (Cao et al., 2025), and the ratio of newly failed nodes across consecutive time steps (Chen et al., 2025). Local metrics such as clustering coefficient (Ma et al., 2025b; Zhou et al., 2025) and local efficiency (Barati et al., 2024) are also widely used. In contrast, performance-based analyses overcome the limitations of purely topological models by integrating the functional characteristics of land transport networks, such as traffic flow (He et al., 2021; Li et al., 2025b), travel demand (Wang et al., 2023b), accessibility (Cao et al., 2025; Wang et al.,

2022), load capacity (Zeng et al., 2025), and road conditions (Jin et al., 2025), thereby providing evaluations more aligned with real-world operational dynamics. Finally, in comprehensive recognition methods, algorithms such as PageRank (Dehaghani and Morency, 2025), k-shell (Wang et al., 2024c; Xiao and Ren, 2024), and TOPSIS (Wang et al., 2025) are widely applied. These techniques balance intrinsic node attributes with contextual structural influences, emphasizing not only the number of neighboring nodes but also their relative importance within the network.

Additionally, a range of alternative theories and methods have been applied to the identification of critical segments, enriching both the indicator set and analytical processes. These include seepage theory (Xiao et al., 2025), graph attention networks (Ye and Luo, 2021), time-series graph analysis (Tian et al., 2021), causal reasoning (Deng et al., 2023; Zhang et al., 2021b), Bayesian networks (Tang and Huang, 2019), Bayesian game (Hou et al., 2025), the gravity model (Li et al., 2025a), and the well-being ability approach (Sarma et al., 2025). Beyond theoretical frameworks, several studies propose data-driven algorithms. For example, Xu et al. (2018) ranked node importance using vehicle trajectory data with the origin-destination entropy and flow (ODEF) and cross-rank (CRRank) algorithms, avoiding reliance on static topological structures. Similarly, Huang et al. (2025) incorporated passenger flow, node attributes, and adjacent node influences into the AIE-D algorithm, which identifies critical nodes in urban rail transit networks through passenger-flow weighting. Notably, Jing et al. (2020) introduced a method for identifying critical subway stations

Table 8 – Mathematical formulation and performance metrics of network evaluation approaches.

Evaluation dimension	Core formula	Variable description	Evaluation focus	Applicable scenario	Representative literature
Vulnerability (topological)	$V = \frac{E_{\text{global}}(G')}{E_{\text{global}}(G)}$ $E_{\text{global}}(G) = \frac{1}{N(N-1)} \sum_{i \neq j} \frac{1}{d_{ij}}$	V: vulnerability indicator E_{global} : global efficiency G' : network after attack G : network before attack d_{ij} : shortest path between nodes i and j N : total number of network nodes	Network efficiency retention capability after attack	Metro network, road network	Yang et al. (2015)
Robustness (functional)	$R = \frac{1}{N} \sum_{t=1}^T \frac{\sum_i \delta_i(t) Q_i(t)}{Q_{\text{total}}}$	R: robustness indicator N : total number of network nodes T : total duration $\delta_i(t)$: whether node i is normal at time t $Q_i(t)$: flow at node i at time t Q_{total} : total flow	Functional maintenance capability under dynamic flow conditions	Multimodal transport network	He et al. (2021)
Reliability (probabilistic)	$\Phi = \Pr(\cap_{i=1}^m (L_i \leq C_i))$ $\Phi \approx \prod_{i=1}^m \phi_i$	Φ_i : reliability of node i L_i, C_i : load and capacity random variables	Probability of maintaining service under multiple disturbances	Road network, attack scenarios	Chen et al. (2024c)
Resilience (dynamic recovery)	$R = \frac{\int_{t_0}^{t_r} P(t) dt}{P_0(t_r - t_0)}$	R: resilience indicator $P(t)$: system performance at time t P_0 : initial performance t_0, t_r : disturbance start and recovery times	Integral area of performance over time, reflecting the entire system recovery process	Transportation networks after disasters	Liu et al. (2022a)
Node criticality identification	$I_i = \frac{1}{N_{\text{OD}}} \sum_{r,s} \frac{\sigma_{rs}(i)}{\sigma_{rs}}$	I_i : the importance of node i N_{OD} : total number of OD pairs $\sigma_{rs}(i)$: number of shortest paths passing through node i σ_{rs} : number of shortest paths between OD pair (r, s)	Node criticality assessment based on path redundancy	Critical station identification in metro networks	Jing et al. (2020)

based on route redundancy, which evaluates effective OD connections from the passenger's perspective during potential disruptions. Their findings showed that critical stations are not necessarily transfer hubs or nodes with high degree centrality. Moreover, stations identified as important by intermediary measures, passenger-flow analysis, and network efficiency indicators do not always correspond to those critical for maintaining network redundancy.

In addition to identifying critical segments, scholars have also explored the key factors that influence drive or intensify failures in land transport networks, deepening the understanding of their dynamic mechanisms. Extensive research highlights the influence of network topology (Li et al., 2019a), cross-network coupling (Abdel-Mottaleb and Zhang, 2020; Fu and Wei, 2023; Li et al., 2025c), environmental disturbances (Chen et al., 2024a; Coar et al., 2021; Guo et al., 2025c; Jana et al., 2025), traffic distribution (Huang et al., 2018), and information control mechanisms (Chen et al., 2024d; Perez and Pereira, 2021). For example, Ma et al. (2020b) examined the impact of severe air pollution on urban rail systems, demonstrating that dynamic vehicle restrictions significantly alter network vulnerability. Similarly, Yang et al. (2023) analyzed cascading failures in subway networks under extreme rainfall, focusing on cross-impact relationships among critical events. Their findings revealed that efficient rescue operations and timely shutdown notifications were the most decisive causal factors in controlling failure propagation. Moreover, they identified that the events with the greatest potential consequences, measured by casualties, property damage, and social disruption, were shutdown notifications, humanitarian response, and public opinion management, respectively.

This paper also compares the key metrics and their mathematical definitions used to assess network vulnerability, robustness, reliability, resilience, and critical node identification in the evaluation section, as summarized in Table 8.

4.4. Integrated application of vulnerability, robustness, reliability, and resilience metrics in actual studies

An increasing number of actual studies treat vulnerability, robustness, reliability and resilience as complementary rather than interchangeable perspectives on network performance.

Vulnerability describes a system's exposed points of sensitivity prior to disruption, while robustness and resilience characterise its state afterwards. Robustness focuses on immediate functional loss, while resilience tracks subsequent performance degradation and recovery trajectories. Reliability introduces an element of uncertainty by shifting the evaluation dimension from a single outcome to the probability of maintaining acceptable service levels under random perturbations. This distinction is important because resilience does not replace vulnerability. In the reviewed studies, vulnerability was predominantly used to define the type of stress to be applied, while resilience assessed the evolution of performance after stress occurred.

Practical research indicates that integration primarily occurs through a few recurring mechanisms that couple different dimensions within modelling and evaluation workflows. One common approach is a sequential process: first, vulnerability is used to screen disruptive scenarios or targets; then, resilience is calculated based on generated performance curves to quantify recovery dynamics. A second mechanism couples robustness with resilience, treating robustness as the initial performance degradation that sets the starting point of the recovery process, thereby making resilience the dynamic envelope of robustness shocks. A third mechanism is response-based integration assessment, in which robustness is evaluated under operational response assumptions and resilience is realised as the system's adaptive response capability, rather than as a purely passive recovery curve. Table 9 presents exemplary cases of these mechanisms across different network types, enabling readers to observe how identical conceptual dimensions materialise through distinct integration workflows.

The core experiential insight underlying these integration mechanisms is that integration is not simply the superposition of metrics, but rather clarifies the positioning of each dimension within the decision-making sequence. Vulnerability supports scenario construction and the prioritisation of critical elements; robustness enables the quantification of real-time impact and the comparison of severity; and resilience facilitates the evaluation of recovery strategies through time-dependent performance trajectories. When incorporating reliability dimensions, these are typically probabilistically encapsulated beyond interruption or service

Table 9 – Integrated use of vulnerability, robustness, reliability, and resilience metrics in actual studies.

Reference	Network type	Integrated metrics	Integration mechanism	Key insight
Mattsson and Jenelius (2015)	Road	Vulnerability + resilience	Theoretical and empirical link between exposure and recovery dynamics	Establishes conceptual complementarity
Pagani et al. (2019)	Rail	Robustness + resilience	Topological robustness coupled with functional restoration	Robustness as basis for resilience
Xu et al. (2023a)	Road	Robustness + resilience	Response-integrated robustness model linking adaptive operations	Dynamic coupling of robustness and resilience
Bashir et al. (2025)	Road	Vulnerability + resilience	Uses vulnerability to select disruption targets, then measures resilience via service recovery over time	Shows a vulnerability-resilience pipeline: vulnerability for exposure, resilience for recovery

acceptability thresholds, enabling analysts to link recovery trajectories to uncertainties in perturbations and operational conditions. This workflow-oriented integration framework improves the interpretability of results by clarifying the specific purpose of each metric, while also improving the actionability of results by explicitly linking each dimension to specific phases of modelling, assessment and recovery decision-making.

5. Fortifying network resilience: recovery strategies and adaptive enhancement

Recovery research constitutes a core dimension of cascading failure studies, aiming to design effective strategies that mitigate disruption spread and accelerate network functionality restoration. Recovery analyses in land transport systems generally address three interrelated aspects. First, they identify recovery targets and intervention priorities by classifying attack types and failure modes. Second, they formulate diversified recovery strategies that leverage both topological properties and passenger flow distributions, thereby clarifying the applicability and constraints of each approach. Third, they evaluate strategy effectiveness using metrics such as functional retention rate and recovery efficiency, which capture the dynamic evolution of the recovery process and the efficiency of resource allocation. Accordingly, identifying recovery targets, designing adaptive strategies, and assessing recovery performance together form the conceptual core of cascading failure recovery research in transportation networks.

5.1. Attack types and failure modes

In the study of cascading failures in land transport networks, simulation-based analyses are widely used to examine various attack types and failure modes. The most common attack types include random attacks (He et al., 2021; Zhang et al., 2019b), malicious attacks (Candelieri et al., 2019; Song et al., 2025), local attacks (Hu et al., 2016), hybrid attacks (Jiang et al., 2024), static and dynamic attacks (Jia et al., 2025), as well as single versus continuous attacks (Du et al., 2025), and single-point versus multi-point attacks (Ma et al., 2019; Mu et al., 2023). Among these, random and malicious attacks remain the two most prevalent approaches in existing research. Random attacks remove nodes or edges with certain probabilities, representing stochastic disruptions such as equipment malfunctions or accidental outages. In contrast, malicious attacks deliberately target specific nodes or edges, typically selected based on centrality or other network metrics. These attacks are used to evaluate the consequences of intentional disruptions, such as sabotage or terrorism. Local attacks eliminate all nodes and edges within a defined geographic area, mimicking failures triggered by natural disasters. Hybrid attacks combine multiple attack strategies, enabling simultaneous or sequential disruptions across different parts of the network. Static and dynamic attacks differ in adaptability: static attacks follow predetermined configurations, whereas dynamic attacks can be adaptively adjusted in response to

changing network conditions, thereby maximizing their disruptive potential. Single versus continuous attacks distinguish between one-time disruptions and those that persist or recur over time. Single-point versus multi-point attacks describe failures confined to a single node or edge, as opposed to those that simultaneously impact multiple components across the network.

Additionally, scholars have designed and compared a variety of targeted attack strategies tailored to different analytical objectives (Jia et al., 2025; Liu et al., 2020b). For instance, Chen et al. (2024c) examined the cascading failure dynamics of the Shanghai road network using five attack strategies: degree centrality attack, betweenness centrality, eigenvector centrality, closeness centrality, and random attacks. Their findings revealed that closeness centrality-based attacks generated the highest levels of congestion, whereas eigenvector centrality attacks produced the greatest decline in network efficiency. Building on this framework, Aparicio et al. (2022) introduced an additional strategy targeting multimodal hubs, thereby extending the analysis to six distinct attack strategies. Using this expanded framework, they evaluated the robustness of Lisbon's public transport system and concluded that strategies relying on recalculated network metrics exert a greater influence on robustness assessments. Moreover, they observed that node-based failures at stations generally posed greater systemic risks than link-based failures along transit paths. Similarly, Chen et al. (2021) applied four strategies, namely initial degree, recalculated degree, initial betweenness, and recalculated betweenness attacks, to analyze cascading failures in the Wuhan metro system under varying disruption scenarios. Their study further incorporated tolerance parameters and passenger transfer rates to quantify capacity loss. The results demonstrated that malicious attacks inflict significantly more severe damage than random ones, and that node betweenness metrics are particularly effective in identifying vulnerable nodes under malicious attacks conditions.

The topological structure and functional integrity of land transport networks exhibit distinct cascading failure dynamics under heterogeneous attack types, leading to varied failure characteristics. Building on this, scholars have further classified cascading failure modes according to attack types identified in existing studies, with an emphasis on the intrinsic mechanisms of the failures themselves. Based on the evolutionary process, failures can be categorized into initial failures and progressive failures. Based on the scope of impact, they can be divided into local and global failures. From the point of origin, they can be distinguished as single-point or multi-point failures, the latter including multi-site, multi-path, and combined site-link failures.

5.2. Recovery strategy development

Scholars have proposed a wide range of recovery strategies to enhance the resilience of land transport networks. These strategies are generally classified into two categories depending on whether they involve topological modification to the network.

- (1) Topology-altering strategies: these approaches modify the network's structural configuration, for instance by closing low-load nodes or high-load links (Dui et al., 2021), deleting or adding links (Zheng et al., 2023), or reconnecting disrupted components (Zhang et al., 2024c). Such methods offer valuable insights for designing more resilient network topologies.
- (2) Non-topology-altering strategies: these approaches preserve the original network structure but optimize performance through load redistribution and routing adjustments. Typical methods include capacity expansion (Bell et al., 2017; Cats and Jenelius, 2015), traffic rerouting (Shen et al., 2021), multi-directional recovery (Shen et al., 2024), sequential recovery (Dui et al., 2022; Tang and Huang, 2019), random recovery (Li et al., 2019b), regional recovery (Dui et al., 2023), hybrid recovery (Xu et al., 2023b; Zhong et al., 2024), and multi-stage recovery (Cui et al., 2025).

Notably, Zhu et al. (2025) argued that expanding network capacity does not necessarily guarantee performance improvement or delay system collapse. Using a directed traffic infrastructure network and seepage theory, they identified critical bottlenecks and demonstrated that introducing disturbances at both strong and weak bottlenecks can trigger premature collapse. Conversely, enhancing bottleneck capacity produces uncertain effects, sometimes delaying but at other times accelerating the collapse process.

In addition to conventional recovery strategies, some scholars have emphasized the self-recovery capability of nodes. In cascading failure simulations, failed nodes are not permanently removed but are treated as temporarily inoperative components. Once repaired, these nodes can restore the load of adjacent nodes, producing evaluation results that more closely approximate real-world conditions (Guo et al., 2025a). Furthermore, researchers have explored real-time control mechanisms as a means of more effectively mitigating the damage caused by sudden events. For instance, Liu et al. (2019) first introduced the concept of remote control in cascade failure studies, applied adaptive control to the British rail-road multilayer network. Their

findings indicate that generating a limited number of new links within the control layer substantially enhances the resilience of both the control layer and other interconnected layers against cascading failures. Zhang et al. (2024d) proposed a real-time operational control framework based on emergency response capability. This method integrates network topology with dynamic evolution characteristics to block potential failure propagation paths. Unlike qualitative optimization strategies, this approach provides immediate applicability in real-time emergency management, representing a significant advancement in practical recovery research.

Fig. 12 illustrates the recovery characteristics of various transport networks. In public transport systems, disruption recovery is typically divided into two stages: preventive control and emergency repair (Jaber et al., 2025; Liu et al., 2024b). Preventive control focuses on strengthening metro service resilience by identifying disruption sources, estimating delay propagation, analyzing passenger response behavior, and designing robust metro service networks. Emergency repair, by contrast, emphasizes real-time interventions such as rescheduling and bus bridging to evacuate passengers from disrupted metro systems. Practical measures in this stage include deploying bus bridging services, rerouting passengers to alternative rail lines, and intensifying monitoring at critical intersections. Malucelli and Tresoldi (2019) further identified three sub-problems central to managing disruptions in public transport networks: schedule adjustment, vehicle rescheduling, and crew rescheduling. Among these, the bus bridging service has become the most widely adopted strategy in practice. By deploying additional buses to replace disrupted metro connections, this approach effectively reduces passenger accumulation, alleviates congestion risks, and mitigates cascading failure likelihood (Gu et al., 2018; Jin et al., 2016; Liang et al., 2019; Su et al., 2025; Zhang and Lo, 2018).

5.3. Verification of recovery strategy effectiveness

Research on cascading failures in land transport networks typically classifies recovery strategy verification into three

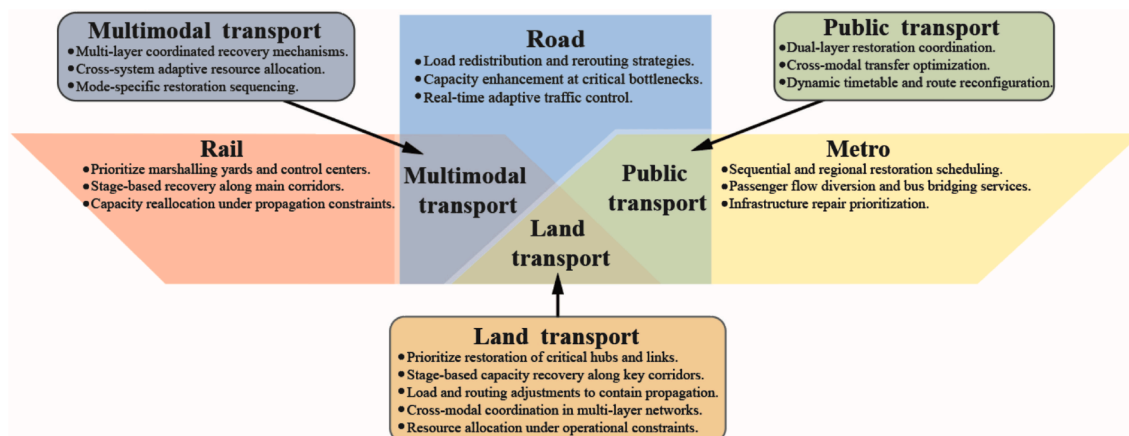


Fig. 12 – Recovery characteristics of cascading failure studies in different types of land transport networks.

categories: structural, functional, and comprehensive. Structural verification emphasizes connectivity restoration as the primary evaluation criterion. These studies track changes in network connectivity during disruption and repair, comparing the speed and robustness of large-scale connectivity recovery under different repair sequences or strategies (Bell et al., 2017). Some extend this by integrating bottleneck identification and network decomposition methods to locate critical nodes or pathways that disproportionately affect connectivity. Simulation experiments then compare strategies such as “priority repair of bottlenecks” versus “random repair”, consistently showing that targeted interventions markedly improve recovery efficiency (Dui et al., 2021). Other studies combine structural verification with load redistribution mechanisms to capture failure propagation dynamics. By simulating restoration under varying targets and timing, they highlight the sensitivity and complexity of recovery pathways (Zhang et al., 2024d). Collectively, these results indicate that verifying recovery effectiveness must move beyond simple topological restoration, integrating the interaction between propagation dynamics and intervention strategies to better reflect real-world recovery processes.

Functional recovery studies focus on restoring transportation service levels, emphasizing the dynamic tracking of demand fulfillment, accessibility, and travel cost. Such studies often use traffic flow allocation models to simulate variations in demand satisfaction, travel efficiency, and service coverage after disruptions, producing recovery trajectory curves for comparative analysis (Ma et al., 2022). In experimental setups, researchers test different repair sequences and resource allocation schemes to observe the shape of recovery curves, thereby identifying strategies that restore service levels more rapidly and effectively (Guo et al., 2023; Zhong et al., 2024). Recent work has introduced dual-layer modeling frameworks, where the upper layer optimizes repair sequence and resource scheduling, while the lower layer models user behavioral responses. This integration yields a comprehensive service recovery trajectory (Guo et al., 2025a). Comparative analyses across different methods consistently demonstrate that repair order, resource deployment efficiency, and construction parallelism play decisive roles in shaping recovery outcomes. Well-designed strategies not only accelerate recovery but also minimize service loss under equivalent constraints.

Comprehensive verification approaches assess the relative performance of different recovery measures through dynamic simulations. A common approach introduces sudden passenger surges or facility overloads to replicate cascading failure propagation. Recovery strategies such as emergency line reconnection, capacity scheduling, and cross-modal integration are then tested comparatively (Zhang et al., 2024c). Simulation results show that proactive or localized interventions, such as early emergency recoupling and redundant scheduling, significantly limit failure propagation and steepen recovery curves, whereas delayed responses often cause resource inefficiency and unstable recovery trajectories. Studies of multi-level transport networks frequently compare spontaneous, proactive, and hybrid recovery strategies by analyzing recovery curve profiles

under varying restoration priorities and timings. Evidence suggests that hybrid strategies consistently outperform single-mode approaches, and that high-load hubs or critical transfer nodes should be prioritized in recovery sequences (Xu et al., 2023b; Zhong et al., 2024). Moreover, cross-system coordination measures such as deploying bus shuttles during metro disruptions have been incorporated into recovery verification frameworks. These analyses confirm that intermodal coordination significantly accelerates system-wide recovery (Liu et al., 2024b; Wang et al., 2023c). In summary, verification of recovery strategies has evolved toward a multidimensional paradigm integrating both structural connectivity and functional serviceability. Through experimental and scenario-based comparisons, studies have revealed systematic differences among strategies in terms of speed, stability, and resource efficiency. Since the ultimate goal of resilience enhancement is effective recovery, this paper provides a comparative analysis of representative recovery strategies, examining their foundational models, operational characteristics, and verification approaches, as summarized in Table 10.

6. Discussions

6.1. Limitations of existing studies

Land transport networks are characterized by high interconnectivity, pronounced heterogeneity, and strong volatility, making them highly susceptible to cascading failures and the amplification of disruptions once failures occur. Over the past decade, scholars have established a relatively systematic framework for investigating such failures. Most studies rely on topological analysis and cascading failure models to explore how node or link disruptions affect overall connectivity and functional performance. Within this framework, multiple analytical dimensions, including vulnerability, robustness, reliability, and resilience, have been widely adopted. From a research paradigm perspective, most studies follow the logical progression of “modeling-evaluation-recovery”. At the modeling stage, emphasis is placed on characterizing propagation mechanisms under external disturbances. The evaluation stage focuses on analyzing network state evolution and identifying critical nodes, while the recovery stage involves proposing strategies for node prioritization, path reconstruction, or resource allocation. Despite these advances, existing research remains constrained in several respects. Most studies continue to depend heavily on static topological analysis and idealized propagation models. Although recent work has begun incorporating factors such as passenger behavior and demand fluctuations, these efforts still rely on simplified assumptions and often neglect interdependencies among influencing factors. Furthermore, empirical validation of such integrative models remains limited, restricting their practical applicability to real-world transport systems. Overall, these limitations can be attributed to the ongoing disparity between models and operations, which impedes the conversion of cascade research findings into practical operational guidelines.

Table 10 – Mathematical models and verification methods of network recovery strategies.

Recovery strategy	Core formula	Variable description	Strategy feature	Verification method	Representative literature
Structural repair (edge addition)	$\max \sum_{i,j \in V} (B_{ij}^{\text{after}} - B_{ij}^{\text{before}})$ s.t. $\sum_{e \in E_{\text{add}}} c_e \leq B$	B_{ij} : betweenness of nodes i and j E_{add} : set of added edges c_e : cost of edge e B : total budget	Edge addition strategy aimed at improving overall network efficiency under budget constraints.	Simulation comparing network efficiency improvement.	Zheng et al. (2023)
Capacity expansion	$\min \sum_i c_i \Delta C_i$ s.t. $L_i(t) \leq C_i + \Delta C_i, \forall i, t$	c_i : unit capacity expansion cost ΔC_i : capacity increment of node i $L_i(t)$: the traffic load on network node i at time t	Minimizing cost while ensuring capacity meets load requirements.	Simulation analyzing load-capacity relationship.	Bell et al. (2017)
Multi-stage recovery optimization	$\min T_{\text{total}} = \sum_{k=1}^K \max_{i \in S_k} t_i^{\text{repair}}$ s.t. $\cup_{k=1}^K S_k = V_{\text{fail}}$	T_{total} : total duration K : total number of stages S_k : set of nodes repaired in stage k t_i^{repair} : time required to repair node i V_{fail} : the set of all failed nodes that require repair after a disruption occurs	Phased recovery strategy minimizing total restoration time.	Simulation comparing different phase division strategies.	Cui et al. (2025)
Real-time control (coupled networks)	$\dot{x}_i = f(x_i) + \epsilon \sum_j A_{ij} (x_j - x_i) + u_i(t)$ $u_i(t) = -k(x_i - x_i^*)$	$\dot{x}_i$: the instantaneous rate of change of node i $f(x_i)$: the intrinsic nonlinear dynamics of node i ϵ : the coupling strength A_{ij} : node adjacency matrix $u_i(t)$: control input k : control gain x_i, x_j : State variables of node i, j x_i^* : desired state	Real-time feedback control based on coupled dynamics, suppressing cascade propagation.	Numerical simulation verifying control effectiveness.	Liu et al. (2019)
Hybrid recovery strategy	$\max \sum_t (\alpha R_{\text{struct}}(t) + \beta R_{\text{func}}(t))$ s.t. resource constraints	R_{struct} : structural recovery degree R_{func} : functional recovery degree α, β : weight coefficients	Multi-objective optimization considering both structural and functional recovery.	Simulation comparing single and hybrid recovery strategies.	Zhong et al. (2024)

The gap between models and operations is evident in the reviewed literature in four specific forms. The first is restricted access to operational data and calibration, which prevents researchers from estimating transmission and recovery parameters from real-world trajectories. Second, computational scalability issues arise, as high-fidelity transmission and recovery models quickly become unmanageable in large-scale, heterogeneous, multi-layer networks. Third, there is behavioural simplification, where traveller adaptation and operator decision-making responses are either omitted or reduced to stylised rules. The fourth form is institutional barriers, including fragmented logging, privacy and proprietary constraints, and inter-agency coordination friction, all of which impede data sharing and implementation.

At the modeling stage, the discrepancies between models and actual operations tend to be particularly pronounced in mainstream paradigms, particularly in load capacity and CML models. In practice, the transportation applications of these models are often limited by three factors: the need for operational data for calibration, the computational burden of large-scale dynamic simulations and the simplified representation of traveller and operator response behaviours. Together, these factors result in significant discrepancies between the modelling process and real-world operational conditions. The load-capacity model assumes that, under static topological conditions, nodes or links fail once their load exceeds capacity thresholds, triggering a progressive cascade. In contrast, the CML model captures state evolution and chaotic characteristics of nonlinear systems, using mapping functions to represent dynamic disturbance amplification. Both models have strong theoretical value in explaining how localized failures escalate into systemic disruptions. Nevertheless, their applicability and explanatory power remain limited. The load-capacity model generally assumes a fixed network structure and static load distribution, making it inadequate for capturing real-world behaviors such as capacity adjustments, traffic diversion, and route optimization. These simplifications stem from limitations in the available data, as there is often insufficient observational data on time-varying capacity, control measures and routing decisions to enable the parameterisation and validation of adaptive dynamic models. Although the CML model better represents nonlinear propagation, it remains highly sensitive to parameter tuning and exhibits limited stability and generalizability when applied to large-scale heterogeneous networks. This sensitivity increases when calibration data is sparse or fragmented, and when computational constraints prevent extensive uncertainty analysis or robust parameter learning under heterogeneous network conditions. In recent years, emerging approaches based on complex network dynamics, multi-agent simulations, and data-driven modeling have shown potential for capturing behavioral heterogeneity and cross-system interactions. However, these methods are still in the exploratory phase and their applicability across different network scenarios is limited.

At the evaluation stage, the gap is further widened by the continued reliance on metrics based on static topologies. This is primarily because high-resolution service and control data is often difficult to obtain and is often scattered across different organisations or challenging to integrate

consistently. These approaches typically employ indicators such as degree centrality, betweenness centrality, and connectivity to evaluate network characteristics under disturbances. While these methods are straightforward and facilitate cross-comparison, they fail to capture a network's operational performance and resilience under complex disruptions and behavioral dynamics. For instance, degree centrality identifies critical nodes solely by the number of their connections, overlooking their roles in passenger flow capacity and path substitution. As a result, it often underestimates operational risks. Similarly, connectivity metrics can determine whether the network remains structurally intact but cannot reflect functional degradation, such as reduced service quality or increased travel times. When networks experience multiple temporally and spatially dispersed disturbances, and passengers continuously adapt their travel plans, results derived from static topology analysis diverge significantly from actual operational performance. Recent studies have attempted to incorporate dynamic factors, such as traffic flow monitoring and time-varying passenger flow patterns, by developing evaluation methods that combine simulation results with real-world data. These efforts have improved the understanding of disturbance propagation mechanisms. However, these efforts are often hindered by incomplete data coverage, inconsistent data standards among operators and limited access to operational control logs. Together, these factors hinder calibration, timely evolution and external verification. Moreover, certain multi-indicator approaches for identifying critical nodes often produce results with limited interpretability, making them difficult to translate into practical guidance for emergency scheduling and resource allocation. This also undermines implementation efforts, since indicators that cannot be interpreted at an operational level are difficult to translate into actionable schedules, setting priorities, or coordinating across agencies.

At the recovery stage, the gap becomes particularly pronounced as most studies continue to focus on node prioritisation, link supplementation and traffic redistribution in idealised scenarios. This is primarily because actual recovery processes are constrained by institutional factors, such as multi-agency coordination, resource ownership, security protocols and service obligations. These elements are difficult to encode and validate within generic cascading models. These methods can theoretically enhance local connectivity or operational efficiency, thereby providing valuable insights for failure management. However, their effectiveness in real-world transport networks remains limited. First, most studies define attack and failure scenarios under idealized assumptions, typically focusing on random or malicious attacks. Such assumptions overlook the complexity of real disturbances, which often involve extreme weather, equipment malfunctions, or sudden surges in passenger demand. Furthermore, the programmatic design of attack scenarios is facilitated by the fact that detailed event logs, scheduling records and resource availability data, which could be used to construct realistic scenarios, are rarely made public or standardised. Consequently, misalignments arise between recovery targets, intervention timing, and operational requirements. Second, the development of recovery strategies often depends on predefined priorities or static repair sequences, which fail to

account for secondary overloads that may occur due to traffic flow redistribution during recovery. While some measures may reduce initial performance losses, they can inadvertently trigger new cascading effects. Third, regarding the verification of recovery effectiveness, although metrics such as functional retention rate and recovery efficiency have been proposed, most studies validate strategies only through simulation experiments. This dependency is further exacerbated by computational constraints. Conducting high-fidelity back-testing across large-scale networks and multiple reasonable control measures would be prohibitively expensive without suitable data pipelines and benchmarking. This limitation reduces their ability to reflect actual system performance in real operational contexts. Overall, despite notable progress in recovery strategy research, significant deficiencies remain in the definition of disturbance scenarios, the formulation of recovery measures, and the verification of their effectiveness. Moreover, recovery research often lacks systematic integration with the modeling and evaluation phases, weakening its practical relevance for emergency management.

At a deeper level, the persistent gap between models and actual operations is driven by two fundamental reasons that define the boundaries of the feasibility of model construction and validation. The first is the recognisability barrier: observed cascading trajectories result from the combined effects of disturbances and operator interventions in practice. This implies that “pure propagation” phenomena rarely occur in the absence of endogenous control responses. Consequently, parameters and behavioural rules become difficult to infer unambiguously, which undermines the validity of out-of-sample validation, especially when severe cascading events are rare and system logs are fragmented. Second is the barrier of socio-technical complexity. Cascade effects stem from the tightly coupled interactions between infrastructure constraints, time-varying capacity, adaptive demand, dispatch rules and institutional priorities. This creates an enormous state-action space that is difficult to model realistically and solve at network scale. These fundamental reasons explain why many studies still adopt manageable simplifications, even when researchers recognise operational limitations.

6.2. Future research directions

This paper highlights the limitations of current research on cascading failures in land transport networks and outlines several future research directions, as illustrated in Fig. 13. A central priority is the development of modeling frameworks capable of capturing multi-factor interactions within transport systems. First, dynamic capacity and traffic diversion mechanisms should be incorporated into cascading failure models. This requires accounting for capacity degradation and progressive recovery during incident response, as well as temporary rerouting and congestion redistribution under peak passenger demand. Such extensions would better represent how fluctuations in operational capacity influence the evolution of cascading failures. Second, the modeling of behavioral feedback mechanisms must be strengthened. Future research should integrate multi-agent simulations or rule-based behavioral models to embed passenger and operator responses within the system's evolutionary logic. This would help reveal the bidirectional interactions between disturbance propagation and adaptive behaviors. Third, improvements should move beyond the isolated exploration of individual model structures, focusing instead on building a flexible, adaptive framework. Automatic parameter calibration can be achieved using trajectory data, passenger flow monitoring, and road sensor information. Moreover, advanced tools such as machine learning and graph neural networks (GNNs) can complement traditional modeling frameworks. For instance, GNNs can dynamically capture evolving interdependencies among traffic subsystems, while integration with time-series forecasting models, such as diffusion convolutional recurrent neural network (DCRNN) and temporal graph attention networks (TGAT), enables more accurate prediction of traffic flow and state transitions. Together, these innovations can enhance the adaptability of models to nonlinear propagation processes and improve their applicability to real-world transport networks.

Regarding evaluation methods, future research should move beyond current limitations, that rely excessively on static topological metrics, insufficiently capture dynamic

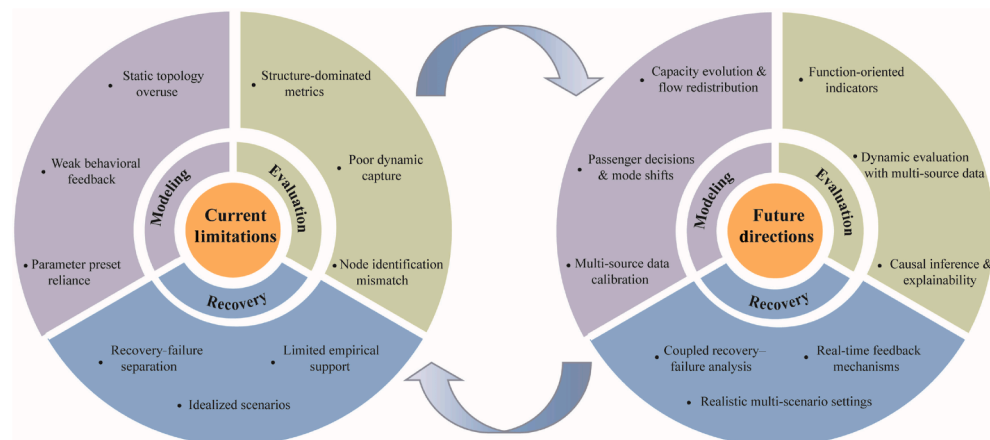


Fig. 13 – Limitations of existing studies and future research directions.

operational patterns, and offer limited interpretability for identifying critical nodes. First, the use of dynamic data should be significantly expanded. Future approaches need to integrate multi-source data from automatic fare collection (AFC), global positioning system (GPS), closed-circuit television (CCTV), and vehicle-to-everything (V2X) systems to capture real-time dynamics such as passenger flow migration, travel delays, and bottleneck congestion. When combined with advanced deep learning models, including long short-term memory (LSTM) networks and Transformer architectures, these data can support more accurate predictions of passenger flow fluctuations and cascading failure trajectories. Second, a multidimensional functional indicator system should be developed. Key indicators such as functional retention rate, service interruption duration, average travel time, and trip completion rate can together provide a comprehensive depiction of how network service capacity evolves across different failure stages. Third, the interpretability of critical node identification must be enhanced. Future studies can integrate causal inference techniques and explainable AI tools, such as Shapley Additive exPlanations (SHAP) and local interpretable model-agnostic explanations (LIME), to clarify how failures at critical nodes trigger traffic shifts or path disruptions. Leveraging big data-driven causal inference will make evaluation results more transparent, reliable, and actionable, thus supporting evidence-based emergency decision-making.

Regarding recovery strategies, the gap between existing research and practical operations is primarily reflected in three aspects: (1) idealized disturbance scenario design, (2) a disconnect between recovery and failure propagation processes, and (3) a lack of real-world validation for verifying effectiveness. Future research should therefore prioritize improvements in these domains. First, scenario design must become more realistic by integrating multi-source data, including historical incident databases, meteorological monitoring, and passenger flow forecasts, supported by AI-driven modeling. Such enriched scenarios would more accurately represent the combined impacts of extreme weather events, equipment failures, and sudden passenger surges. In this context, data-driven models can be developed to identify recovery targets and optimize sequencing. For instance, models trained on large-scale operational datasets could determine which nodes or lines to prioritize under resource constraints, thereby facilitating the rapid restoration of overall system functionality. Second, it is essential to establish a dynamic coupling mechanism between recovery processes and failure propagation. Future studies can leverage traffic simulation platforms, such as simulation of urban mobility (SUMO) or multi-agent transport simulation (MATSim), to enable real-time evaluation of traffic distribution and capacity status during the recovery process. When integrated with multi-agent reinforcement learning algorithms, this approach can analyze how different recovery sequences influence system evolution. It can also capture the redistribution effects triggered by recovery measures and assess the risk of secondary overload, thereby preventing interventions that alleviate initial losses but inadvertently generate new cascading failures. Furthermore, such mechanisms provide a robust analytical foundation for comparing the relative effectiveness

of alternative recovery strategies. Third, evaluation and feedback mechanisms for assessing recovery effectiveness should be substantially strengthened. Future frameworks need to incorporate operationally metrics such as travel delay reduction, passenger flow restoration rates, resource utilization efficiency, and capacity recovery curves. These indicators should be dynamically updated through the integration of real-world measurements and simulation-based outputs. By combining real-time big data collection with machine learning methods to extract key operational patterns, researchers can enable continuous monitoring and iterative optimization of recovery outcomes.

Based on the limitations summarised in Fig. 13 and the two major structural obstacles identified, future research may adopt data model decision verification methods to ensure repeatability and operational feasibility in calibration and evaluation. Firstly, a scenario library should be created using historical event logs and risk footprints to ensure that the intensity, duration and spatial correlation of disturbances reflect actual operational conditions. Secondly, data assimilation or Bayesian inference methods should be employed to calibrate and update key parameters and behavioural rules, thereby quantifying uncertainty and enhancing identifiability. Data sources should encompass multiple operational streams, such as automated toll records, GPS trajectories, detector measurements and logs of accessible control actions, such as dispatch instructions and signal control. Thirdly, strategies should be restored through historical event backtesting, sensitivity analysis of reasonable control measures and uncertainty quantification assessments, replacing point estimates with confidence intervals. This process should produce reproducible results, including open-source scenario specifications, parameter prior and posterior distributions, calibration fit reports and historical event benchmarks with uncertainty intervals. Finally, embedding the validated model in a digital twin or a decision support workflow co-designed with operators will enable coordination between modelled state variables and operational levers, such as scheduling, rerouting and phased recovery. This enhances the model's practical relevance and application scalability.

7. Conclusions

This paper provides a systematic review of research progress on cascading failures in land transport networks. Existing studies have gradually established a comprehensive technical framework spanning three dimensions: modeling, evaluation, and recovery. In terms of modeling, the load-capacity and CML models remain the most widely applied. Recent studies have also explored multi-agent simulations and data-driven approaches to better capture complex behaviors and cross-system interactions. In terms of evaluation, indicator systems have evolved beyond static topological metrics to include functional and dynamic dimensions. Several studies have further incorporated traffic flow data into evaluation frameworks to more realistically reflect network performance during disturbances. Regarding recovery, researchers have proposed diverse strategies and examined their effectiveness

across structural, functional, and integrated perspectives. Despite these advances, significant gaps remain between academic research and real-world practice. Modeling approaches still rely heavily on static topologies and idealized propagation rules, limiting their ability to capture the combined influences of capacity evolution, traffic regulation, and passenger behavioral adaptation. Evaluation methods, though broadened, remain overly dependent on structural indicators, making them insufficient for describing system dynamics during disruptions. Recovery strategies are largely based on simulation experiments and lack systematic integration with failure propagation mechanisms. Moreover, the verification of recovery effectiveness remains limited due to the scarcity of empirical operational data. These constraints are further exacerbated by the difficulty of achieving computational scalability, as well as institutional barriers to data sharing and cross-agency coordination.

This paper highlights several directions for advancing future research. First, models should more comprehensively integrate traffic diversion, capacity evolution, and passenger choice behavior to capture realistic dynamic conditions. Second, evaluation should increasingly focus on dynamic datasets and functional performance metrics, supported by multidimensional indicator frameworks. Third, both the accuracy and interpretability of predictions should be enhanced through the integration of causal inference techniques and explainable AI methods. With regard to recovery, future studies should be firmly grounded in real-world data to construct multi-source disturbance scenarios. Recovery strategies should explicitly incorporate the interaction between recovery actions and cascading propagation, supported by real-time evaluation and adaptive correction mechanisms informed by operational data. Although the conceptual foundation draws on pioneering research from before 2015 and cross-validates findings through a comparative analysis of literature, restricting the quantitative distribution to the period from 2015 to 2025 may underestimate the significance of earlier foundational research. This consequently restricts the historical completeness of the analysis. Finally, this review primarily addresses macro-level transport networks and does not systematically cover insights at the route or vehicle level. Consequently, it does not fully capture advancements in localized failure analysis. Future work should aim to bridge macro- and micro-level perspectives, thereby achieving a more comprehensive understanding of cascading failures in land transport systems.

Conflict of interest

The authors do not have any conflict of interest with other entities or researchers.

CRedit authorship contribution statement

Wei Ren: Writing – original draft, Methodology. **Fei Ma:** Supervision, Funding acquisition. **Zhen Shang:** Software, Resources. **Lei Wang:** Formal analysis. **Wenjun Liu:** Visualization. **Qing Liu:**

Writing – review & editing. **Jinghui Li:** Conceptualization. **Joonho Ko:** Supervision, Conceptualization.

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REFERENCES

- Abdel-Mottaleb, N., Zhang, Q., 2020. Water distribution-transportation interface connectivity responding to urban geospatial morphology. *Journal of Infrastructure Systems* 26 (3), 04020025.
- Albert, R., Jeong, H., Barabási, A.L., 2000. Error and attack tolerance of complex networks. *Nature* 406, 378–382.
- Aparicio, J.T., Arsenio, E., Henriques, R., 2022. Assessing robustness in multimodal transportation systems: a case study in Lisbon. *European Transport Research Review* 14 (1), 28.
- Bai, H., Zhang, D., Guo, J., et al., 2025. Resilience of metro systems subjected to external disturbances: a state-of-the-art review. *Resilient Cities and Structures* 4 (4), 72–96.
- Barabási, A.L., Albert, R., 1999. Emergence of scaling in random networks. *Science* 286 (5439), 509–512.
- Barati, H., Yazici, A., Almotahari, A., 2024. A methodology for ranking of critical links in transportation networks based on criticality score distributions. *Reliability Engineering & System Safety* 251, 110332.
- Bashir, T., Bergantino, A.S., Troiani, V., et al., 2025. Vulnerability and resilience analysis of road transport infrastructure: a bibliometric analysis of global trends and future research agenda. *Sustainable Futures* 10, 101142.
- Bell, M.G.H., Kurauchi, F., Perera, S., et al., 2017. Investigating transport network vulnerability by capacity weighted spectral analysis. *Transportation Research Part B: Methodological* 99, 251–266.
- Bin Wee, X., Herrera, M., Hadjidemetriou, G.M., et al., 2023. Simulation and criticality assessment of urban rail and interdependent infrastructure networks. *Transportation Research Record* 2677, 1181–1196.
- Boccaletti, S., Latora, V., Moreno, Y., et al., 2006. Complex networks: structure and dynamics. *Physics Reports* 424, 175–308.
- Buldyrev, S.V., Parshani, R., Paul, G., et al., 2010. Catastrophic cascade of failures in interdependent networks. *Nature* 464, 1025–1028.
- Candelieri, A., Galuzzi, B.G., Giordani, I., et al., 2019. Vulnerability of public transportation networks against directed attacks and cascading failures. *Public Transport* 11, 27–49.
- Cao, Y., Bu, X., Zhang, J., 2025. Robustness evaluation of bus-subway composite network considering accessibility. *Scientific Reports* 15, 10770.
- Cao, N., Cao, H., 2020. Exploring the robustness of urban bus network: a case from Southern China. *Chinese Journal of Physics* 65, 389–397.
- Cats, O., Jenelius, E., 2015. Planning for the unexpected: the value of reserve capacity for public transport network robustness. *Transportation Research Part A: Policy and Practice* 81, 47–61.

- Chen, S., Chi, X., Zhang, Q., et al., 2024b. Cascading reliability assessment of international railway freight network based on coupled map lattices: a case study of China railway express. *Journal of Advanced Transportation* 2024 (1), 1436605.
- Chen, B., Hu, S., Xu, X., et al., 2026. A survey of multi-modal urban transportation network resilience: modeling, evaluation, and optimization. *Transportation Research Part E: Logistics and Transportation Review* 207, 104634.
- Chen, G., Van Woensel, T., Xu, J., et al., 2024d. Assessing movement-specific resilience of a signalized road network under lane-level cascading failure. *Physica A: Statistical Mechanics and its Applications* 654, 130154.
- Chen, B., Wu, J., Chen, Y., et al., 2025. Cascading failures in interdependent transportation networks: a generalized coupled map lattice model with intermodal dynamics. *Physica A: Statistical Mechanics and its Applications* 675, 130836.
- Chen, H., Zhang, L., Liu, Q., et al., 2021. Simulation-based vulnerability assessment in transit systems with cascade failures. *Journal of Cleaner Production* 295, 126441.
- Chen, Z., Zheng, C., Tao, T., et al., 2024c. Reliability analysis of urban road traffic network under targeted attack strategies considering traffic congestion diffusion. *Reliability Engineering & System Safety* 248, 110171.
- Chen, Z., Zheng, C., Xu, M., et al., 2024a. Quantitative assessment of congestion diffusion and cascading effect under rainfall-flood disasters: a case study of Nanjing, China. *International Journal of Disaster Risk Reduction* 114, 104915.
- Cheng, G., Liu, X., Pei, Y., 2023. A review of research on public transport priority based on CiteSpace. *Journal of Traffic and Transportation Engineering (English Edition)* 10 (6), 1118–1147.
- Coar, M., Sarreshtehdari, A., Garlock, M., et al., 2021. Methodology and challenges of fire following earthquake analysis: an urban community study considering water and transportation networks. *Natural Hazards* 109 (1), 1–31.
- Cui, X., Li, B., Zhang, S., et al., 2025. Resilience-based restoration sequence optimization of disrupted transportation networks: a novel matheuristic approach. *Transportation Research Part D: Transport and Environment* 145, 104834.
- Darayi, M., Barker, K., Santos, J.R., 2017. Component importance measures for multi-industry vulnerability of a freight transportation network. *Networks Spatial Economics* 17, 1111–1136.
- Dehaghani, K.R., Morency, C., 2025. Beyond traditional metrics: redefining urban metro network vulnerability with redundancy assessment. *Physica A: Statistical Mechanics and its Applications* 664, 130461.
- Deng, Y., Liu, S., Zhou, D., 2023. Dependency cluster analysis of urban road network based on percolation. *Transportation Research Part C: Emerging Technologies* 154, 104264.
- Ding, X., Hu, H., Liu, Z., et al., 2024. The spatiotemporal evolution mechanism of urban rail transit fault propagation in networked operation modes. *Urban Rail Transit* 10 (1), 65–88.
- Ding, M., Zhu, T., Lian, W., et al., 2025. Assessing operational impacts of large-scale disruptions in urban rail transit: an improved multilayer interdependent network cascading failure model by data calibration. *Transportation Research Part E: Logistics and Transportation Review* 202, 104314.
- Dong, S., Gao, X., Mostafavi, A., et al., 2023. Characterizing resilience of flood-disrupted dynamic transportation network through the lens of link reliability and stability. *Reliability Engineering & System Safety* 232, 109071.
- Dong, S., Yu, T., Farahmand, H., et al., 2020. Probabilistic modeling of cascading failure risk in interdependent channel and road networks in urban flooding. *Sustainable Cities and Society* 62, 102398.
- Du, J., Cui, J., Ren, G., et al., 2025. Cascading failures and resilience evolution in urban road traffic networks with bounded rational route choice. *Physica A: Statistical Mechanics and its Applications* 664, 130456.
- Duan, J., Li, D., Huang, H., 2023. Reliability of the traffic network against cascading failures with individuals acting independently or collectively. *Transportation Research Part C: Emerging Technologies* 147, 104017.
- Dui, H., Chen, S., Wang, J., 2021. Failure-oriented maintenance analysis of nodes and edges in network systems. *Reliability Engineering & System Safety* 215, 107894.
- Dui, H., Yang, Y., Zhang, Y., et al., 2022. Recovery analysis and maintenance priority of metro networks based on importance measure. *Mathematics* 10 (21), 3989.
- Dui, H., Zhang, Y., Chen, L., et al., 2023. Cascading failures and maintenance optimization of urban transportation networks. *Eksplotacja i Niezawodność—Maintenance and Reliability* 25 (3), 168826.
- Fan, Y., Zhang, F., Jiang, S., et al., 2020. Dynamic robustness analysis for subway network with spatiotemporal characteristic of passenger flow. *IEEE Access* 8, 45544–45555.
- Fu, W., Wei, M., 2023. Electric vehicle charging path planning considering coupled faults in distribution-transportation network. *Frontiers in Energy Research* 11, 1206749.
- Gao, C., Fan, Y., Jiang, S., et al., 2021. Dynamic robustness analysis of a two-layer rail transit network model. *IEEE Transactions on Intelligent Transportation Systems* 23 (7), 6509–6524.
- Gu, W., Yu, J., Ji, Y., et al., 2018. Plan-based flexible bus bridging operation strategy. *Transportation Research Part C: Emerging Technologies* 91, 209–229.
- Guan, X., Chen, C., 2018. General methodology for inferring failure-spreading dynamics in networks. *Proceedings of the National Academy of Sciences* 115 (35), E8125–E8134.
- Guo, X., Du, Q., Li, Y., et al., 2023. Cascading failure and recovery of metro-bus double-layer network considering recovery propagation. *Transportation Research Part D: Transport and Environment* 122, 103861.
- Guo, X., Du, Q., Li, Y., et al., 2025a. Cascading failure and recovery propagation of metro-bus double-layer network under time-varying passengers. *Transportation Research Part D: Transport and Environment* 139, 104571.
- Guo, J., Liang, Q., Zhao, J., 2025b. Traffic network: a cascade fault-oriented flow allocation method. *Physica A: Statistical Mechanics and its Applications* 661, 130394.
- Guo, C., Tang, J., Hong, J., et al., 2025c. Resilience assessment of urban bus-metro system to floods under future climate change. *Transportation Research Part D: Transport and Environment* 148, 104925.
- Guo, X., Wang, D., Wu, J., et al., 2020b. Mining commuting behavior of urban rail transit network by using association rules. *Physica A: Statistical Mechanics and its Applications* 559, 125094.
- Guo, J., Xu, J., He, Z., et al., 2020a. Simulation study on cascading failure of multimodal transport network. *Journal of Advanced Transportation* 2020 (1), 3976910.
- Hassan, R., Yosri, A., Ezzeldin, M., et al., 2022. Robustness quantification of transit infrastructure under systemic risks: a hybrid network-analytics approach for resilience planning. *Journal of Transportation Engineering, Part A: Systems* 148 (10), 04022089.
- He, Y., Lin, H., Yang, L., et al., 2025. Generative models for the evolution of transportation systems. *Journal of Traffic and Transportation Engineering (English Edition)* 12 (6), 1784–1803.
- He, Z., Navneet, K., Van Dam, W., et al., 2021. Robustness assessment of multimodal freight transport networks. *Reliability Engineering & System Safety* 207, 107315.
- Hou, B., Chen, P., Zhao, X., et al., 2025. Optimal allocation of defensive resources in regional railway networks under intentional attacks. *Reliability Engineering & System Safety* 257, 110864.
- Hu, X., Huang, J., Shi, F., 2022. A robustness assessment with passenger flow data of high-speed rail network in China. *Chaos, Solitons & Fractals* 165, 112792.

- Hu, Z., Yang, J., Chang, S., et al., 2025. Robustness analysis of bus-rail multilayer network based on dynamic passenger flow. *Reliability Engineering & System Safety* 264, 111403.
- Hu, F., Yeung, C., Yang, S., et al., 2016. Recovery of infrastructure networks after localised attacks. *Scientific Reports* 6, 24522.
- Huang, W., Chen, X., Pu, H., et al., 2025. Using AIE-D algorithm to recognize the node importance of weighted urban rail transit network considering passenger flow. *Information Sciences* 711, 122106.
- Huang, J., Zhou, F., Xi, M., 2018. Calculation method for load capacity of urban rail transit station considering cascading failure. *Journal of Advanced Transportation* 2018 (1), 6318516.
- Jaber, S., Ameli, M., Mahdavi, S.M.H., et al., 2025. A methodological framework for resilience as a service (RaaS) in multimodal urban transportation networks. *Sustainable Cities and Society* 124, 106276.
- Jana, D., Malama, S., Szasdi-Bardales, F., et al., 2025. Improving wildfire resilience of road networks through generative models. *Reliability Engineering & System Safety* 264, 111429.
- Ji, W., Yuan, Q., Cheng, G., et al., 2023. Traffic accidents of autonomous vehicles based on knowledge mapping: a review. *Journal of Traffic and Transportation Engineering (English Edition)* 10 (6), 1061–1073.
- Jia, H., Li, F., Yang, L., et al., 2020. Dynamic cascading failure analysis in congested urban road networks with self-organization. *IEEE Access* 8, 17916–17925.
- Jia, W., Zhang, K., Ma, X., et al., 2025. Resilience assessment for bus-metro multimodal networks considering various attacking scenarios. *Multimodal Transportation* 4 (4), 100238.
- Jiang, R., Lu, Q., Peng, Z., 2018. A station-based rail transit network vulnerability measure considering land use dependency. *Journal of Transport Geography* 66, 10–18.
- Jiang, J., Wu, L., Yu, J., et al., 2024. Robustness of bilayer railway-aviation transportation network considering discrete cross-layer traffic flow assignment. *Transportation Research Part D: Transport and Environment* 127, 104071.
- Jiao, J., Zhang, F., Liu, J., 2020. A spatiotemporal analysis of the robustness of high-speed rail network in China. *Transportation Research Part D: Transport and Environment* 89, 102584.
- Jin, J., Teo, K.M., Odoni, A.R., 2016. Optimizing bus bridging services in response to disruptions of urban transit rail networks. *Transportation Science* 50 (3), 790–804.
- Jin, K., Wang, W., Li, X., et al., 2022a. Exploring the robustness of public transportation system on augmented network: a case from Nanjing China. *Physica A: Statistical Mechanics and its Applications* 608, 128252.
- Jin, K., Wang, W., Li, X., et al., 2022b. Identifying the critical road combination in urban roads network under multiple disruption scenarios. *Physica A: Statistical Mechanics and its Applications* 607, 128192.
- Jin, K., Wang, W., Li, X., et al., 2023. Cascading failure in urban rail transit network considering demand variation and time delay. *Physica A: Statistical Mechanics and its Applications* 630, 129290.
- Jin, Z., Wang, Y., Meng, X., et al., 2025. Identifying critical roads in urban road networks considering congestion propagation. *Physica A: Statistical Mechanics and its Applications* 675, 130795.
- Jing, W., Xu, X., Pu, Y., 2020. Route redundancy-based approach to identify the critical stations in metro networks: a mean-excess probability measure. *Reliability Engineering & System Safety* 204, 107204.
- Jung, S., Lee, S., Kwon, O., et al., 2020. Grid-based traffic vulnerability analysis by using betweenness centrality. *Journal of the Korean Physical Society* 77, 538–544.
- Kays, H.M.I., Sadri, A.M., Muraleetharan, K., et al., 2024. Exploring the interdependencies between transportation and stormwater networks: the case of Norman, Oklahoma. *Transportation Research Record* 2678, 491–513.
- Kays, H.M.I., Sadri, A.M., Muraleetharan, K., et al., 2025. Modeling flood propagation and cascading failures in interdependent transportation and stormwater networks. *International Journal of Critical Infrastructure Protection* 48, 100741.
- Kibar, F.T., Betusb, Y., Tuydes-Yaman, H., 2025. Defining transportation systems resilience under natural disasters: a bibliometric analysis based on mode, metrics and scope. *Transportation Research Procedia* 90, 282–289.
- Lei, H., Hua, X., Yu, W., et al., 2025. Analysis of cascading failure in urban metro networks: a dynamic perspective incorporating changes in travel decisions. *Journal of Advanced Transportation* 2025 (1), 5576254.
- Li, X., Guo, J., Gao, C., et al., 2018. Network-based transportation system analysis: a case study in a mountain city. *Chaos, Solitons & Fractals* 107, 256–265.
- Li, W., Han, Y., Wang, P., et al., 2019a. Invulnerability analysis of traffic network in tourist attraction under unexpected emergency events based on cascading failure. *IEEE Access* 7, 147383–147398.
- Li, D., Hou, Y., Du, S., et al., 2024a. Cascading failure and resilience of urban rail transit stations under flood conditions: a case study of Shanghai metro. *Water* 16 (19), 2731.
- Li, Z., Jin, C., Hu, P., et al., 2019b. Resilience-based transportation network recovery strategy during emergency recovery phase under uncertainty. *Reliability Engineering & System Safety* 188, 503–514.
- Li, J., Lu, Q., Xu, P., et al., 2024b. Cascading failures on multimodal public transportation networks: the role of station coupling strength. *IEEE Transactions on Intelligent Transportation Systems* 25 (11), 17187–17199.
- Li, J., Lu, Q., Xu, P., et al., 2025a. Critical station identification for cascading failure mitigation considering the Lyapunov-stability of metro stations. *Reliability Engineering & System Safety* 256, 110772.
- Li, X., Teng, M., Jiang, S., et al., 2025b. A dynamic station-line centrality for identifying critical stations in bus-metro networks. *Chaos, Solitons & Fractals* 194, 116102.
- Li, C., Yang, Z., Zhu, Y., 2021. Invulnerability simulation of urban agglomeration passenger transport network under incomplete information attack strategy. *Advances in Civil Engineering* 2021 (1), 6658299.
- Li, S., Zhou, Y., Zhang, F., 2025c. Interdependency in transportation system resilience: review and discussion. *Transportation Research Part D: Transport and Environment* 140, 104618.
- Liang, J., Wu, J., Qu, Y., et al., 2019. Robust bus bridging service design under rail transit system disruptions. *Transportation Research Part E: Logistics and Transportation Review* 132, 97–116.
- Lin, S., Jia, L., Zhang, H., et al., 2025. Failure propagation analysis of high-speed train systems from the perspective of multi-layer stochastic flow network. *Reliability Engineering & System Safety* 265, 111510.
- Lin, X., Lu, Q., Chen, L., et al., 2024. Assessing dynamic congestion risks of flood-disrupted transportation network systems through time-variant topological analysis and traffic demand dynamics. *Advanced Engineering Informatics* 62, 102672.
- Liu, Z., Chen, H., Liu, E., et al., 2022a. Exploring the resilience assessment framework of urban road network for sustainable cities. *Physica A: Statistical Mechanics and its Applications* 586, 126465.
- Liu, Z., Chen, H., Liu, E., et al., 2022b. Evaluating the dynamic resilience of the multi-mode public transit network for sustainable transport. *Journal of Cleaner Production* 348, 131350.
- Liu, R., Jia, C., Lai, Y., 2019. Remote control of cascading dynamics on complex multilayer networks. *New Journal of Physics* 21 (4), 045002.

- Liu, Y., Li, K., Feng, T., et al., 2024a. Novel approach for quantifying the propagation of subway equipment faults by using multimodal networks. *Transportation Research Record* 2678, 1058–1082.
- Liu, Z., Sun, D., Chen, H., et al., 2024b. Resilience-based post-disaster repair strategy for integrated public transit networks. *Transportmetrica B: Transport Dynamics* 12 (1), 1–25.
- Liu, S., Yin, C., Chen, D., et al., 2020b. Modelling and impact analysis of interdependent characteristics on cascading overload failure of syncretic railway networks. *PloS ONE* 15 (9), e0239096.
- Liu, J., Yu, W., Yang, M., et al., 2026. Generative AI for transportation safety and resilience: a comprehensive review from a lifecycle perspective. *Safety Science* 196, 107090.
- Liu, Z., Yu, B., Zhang, L., et al., 2025. Resilience enhancement of multi-modal public transportation system via electric bus network redesign. *Transportation Research Part E: Logistics and Transportation Review* 193, 103810.
- Liu, B., Zhu, G., Li, X., et al., 2020a. Vulnerability assessment of the urban rail transit network based on travel behavior analysis. *IEEE Access* 9, 1407–1419.
- Lu, Q., 2018. Modeling network resilience of rail transit under operational incidents. *Transportation Research Part A: Policy and Practice* 117, 227–237.
- Lu, Q., Li, J., Xu, P., et al., 2024. Modeling cascading failures of urban rail transit network based on passenger spatiotemporal heterogeneity. *Reliability Engineering & System Safety* 242, 109726.
- Lu, Y., Yi, M., Cui, J., et al., 2025. Assessment of urban rail transit network passenger-centered resilience under hazards: a dynamic resilience assessment framework. *Accident Analysis & Prevention* 217, 108042.
- Lu, Q., Zhang, L., Xu, P., et al., 2022. Modeling network vulnerability of urban rail transit under cascading failures: a coupled map lattices approach. *Reliability Engineering & System Safety* 221, 108320.
- Ma, Z., Hu, D., Chien, S.I.J., et al., 2025a. Robustness of urban rail transit networks considering cascade failure under attacks: a case study of Nanjing, China. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering* 11 (1), 04024093.
- Ma, F., Liang, Y., Yuen, K.F., et al., 2020b. Assessing the vulnerability of urban rail transit network under heavy air pollution: a dynamic vehicle restriction perspective. *Sustainable Cities and Society* 52, 101851.
- Ma, Z., Liu, J., Chien, S.I.J., et al., 2023b. Identifying critical stations affecting vulnerability of a metro network considering passenger flow and cascading failure: case of Xi'an Metro in China. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering* 9 (2), 04023014.
- Ma, F., Liu, F., Yuen, K.F., et al., 2019. Cascading failures and vulnerability evolution in bus-metro complex bilayer networks under rainstorm weather conditions. *International Journal of Environmental Research and Public Health* 16 (3), 329.
- Ma, F., Shi, W., Yuen, K.F., et al., 2020a. Exploring the robustness of public transportation for sustainable cities: a double-layered network perspective. *Journal of Cleaner Production* 265, 121747.
- Ma, Z., Yang, X., Chen, A., et al., 2025b. Assessing the resilience of multi-modal transportation networks with the integration of urban air mobility. *Transportation Research Part A: Policy and Practice* 195, 104465.
- Ma, Z., Yang, X., Wu, J., et al., 2022. Measuring the resilience of an urban rail transit network: a multi-dimensional evaluation model. *Transport Policy* 129, 38–50.
- Ma, X., Zhu, C., Wang, Z., et al., 2023a. Cascade failure evolution of bilayer rail transit network considering station resistance characteristics. *IAENG International Journal of Applied Mathematics* 53 (2), 1–14.
- Malucelli, F., Tresoldi, E., 2019. Delay and disruption management in local public transportation via real-time vehicle and crew re-scheduling: a case study. *Public Transport* 11 (1), 1–25.
- Mattsson, L.G., Jenelius, E., 2015. Vulnerability and resilience of transport systems—a discussion of recent research. *Transportation Research Part A: Policy and Practice* 81, 16–34.
- Motter, A.E., Lai, Y., 2002. Cascade-based attacks on complex networks. *Physical Review E* 66, 065102.
- Mu, N., Xin, P., Wang, Y., et al., 2023. Vulnerability analysis of China's air and high-speed rail composite express network under different node attack strategies. *Annals of Operations Research* 2023, 1–35.
- Newman, M.E.J., 2003. The structure and function of complex networks. *SIAM Review* 45, 167–256.
- Nie, Y., Li, J., Liu, G., et al., 2023. Cascading failure-based reliability assessment for post-seismic performance of highway bridge network. *Reliability Engineering & System Safety* 238, 109457.
- Pagani, A., Mosquera, G., Alturki, A., et al., 2019. Resilience or robustness: identifying topological vulnerabilities in rail networks. *Royal Society Open Science* 6 (2), 181301.
- Perez, Y., Pereira, F.H., 2021. Simulation of traffic light disruptions in street networks. *Physica A: Statistical Mechanics and its Applications* 582, 126225.
- Qian, Y., Wang, B., Xue, Y., et al., 2015. A simulation of the cascading failure of a complex network model by considering the characteristics of road traffic conditions. *Nonlinear Dynamics* 80, 413–420.
- Sarma, H.D., Teixeira, R., Sangeeta, S., et al., 2025. An overview of the capability approach in wellbeing-focused transport network criticality assessment. *Transportation Research Interdisciplinary Perspectives* 31, 101443.
- Shen, Y., Ren, G., Ran, B., 2021. Cascading failure analysis and robustness optimization of metro networks based on coupled map lattices: a case study of Nanjing, China. *Transportation* 48 (2), 537–553.
- Shen, Y., Ren, G., Ran, B., 2022. Analysis of cascading failure induced by load fluctuation and robust station capacity assignment for metros. *Transportmetrica A: Transport Science* 18 (3), 1401–1419.
- Shen, Y., Ren, G., Zhang, N., et al., 2020b. Effects of mutual traffic redistribution on robustness of interdependent networks to cascading failures under fluctuant load. *Physica A: Statistical Mechanics and its Applications* 560, 125138.
- Shen, Y., Song, G., Xu, H., et al., 2020a. Model of node traffic recovery behavior and cascading congestion analysis in networks. *Physica A: Statistical Mechanics and its Applications* 545, 123422.
- Shen, Y., Yang, H., Ren, G., et al., 2024. Model cascading overload failure and dynamic vulnerability analysis of facility network of metro station. *Reliability Engineering & System Safety* 242, 109711.
- Shen, Y., Yang, H., Xie, Y., et al., 2023. Adaptive robustness optimization against network cascading congestion induced by fluctuant load via a bilateral-adaptive strategy. *Physica A: Statistical Mechanics and its Applications* 630, 129229.
- Song, X., Zhao, P., Yin, R., et al., 2025. Cascading failure model and resilience-based sequential recovery strategy for complex networks. *Reliability Engineering & System Safety* 253, 110488.
- Su, Z., Lee, E., Du, K., et al., 2025. Resilient bus services design in a multimodal network with uncertain metro system disruption. *Transportation Research Part C: Emerging Technologies* 174, 105118.

- Sun, G., 2023. Robustness analysis of an urban public traffic network based on a multi-subnet composite complex network model. *Entropy* 25 (10), 1377.
- Sun, J., Bathgate, K., Pan, S., et al., 2024. Network-based method for assessing multi-modal transportation network vulnerability to cascading failures. *Sustainability Analytics and Modeling* 4, 100034.
- Sun, L., Huang, Y., Chen, Y., et al., 2018. Vulnerability assessment of urban rail transit based on multi-static weighted method in Beijing, China. *Transportation Research Part A: Policy and Practice* 108, 12–24.
- Sun, R., Zhu, G., Liu, B., et al., 2022. Vulnerability analysis of urban rail transit network considering cascading failure evolution. *Journal of Advanced Transportation* 2022 (1), 2069112.
- Tak, S., Kim, S., Byon, Y.J., et al., 2018. Measuring health of highway network configuration against dynamic Origin-destination demand network using weighted complex network analysis. *PloS ONE* 13 (11), e0206538.
- Tang, Y., Huang, S., 2019. Assessing seismic vulnerability of urban road networks by a Bayesian network approach. *Transportation Research Part D: Transport and Environment* 77, 390–402.
- Tian, Y., Liu, X., Li, Z., et al., 2021. Identification of critical links in urban road network considering cascading failures. *Mathematical Problems in Engineering* 2021 (1), 9994347.
- Wandelt, S., Shi, X., Sun, X., 2021. Estimation and improvement of transportation network robustness by exploiting communities. *Reliability Engineering & System Safety* 206, 107307.
- Wang, L., An, M., Jia, L., et al., 2019. Application of complex network principles to key station identification in railway network efficiency analysis. *Journal of Advanced Transportation* 2019 (1), 1574136.
- Wang, J., Cai, L., Xu, B., et al., 2016a. Out of control: fluctuation of cascading dynamics in networks. *Physica A: Statistical Mechanics and its Applications* 462, 1231–1243.
- Wang, J., Li, Y., He, H., et al., 2024b. Abnormal cascading dynamics in transportation networks based on Gaussian distribution of load. *Physica A: Statistical Mechanics and its Applications* 654, 130119.
- Wang, D., Liu, H., Szeto, W.Y., et al., 2016b. Identification of critical combination of vulnerable links in transportation networks—a global optimisation approach. *Transportmetrica A: Transport Science* 12 (4), 346–365.
- Wang, Z., Pei, Y., Liu, J., et al., 2023a. Vulnerability analysis of urban road networks based on traffic situation. *International Journal of Critical Infrastructure Protection* 41, 100590.
- Wang, Z., Pei, Y., Zhang, J., et al., 2024a. Vulnerability analysis of public transit systems from the perspective of the traffic situation. *Physica A: Statistical Mechanics and its Applications* 634, 129441.
- Wang, Z., Pei, Y., Zhang, J., et al., 2025. Dynamic vulnerability analysis of multi-modal public transport network using generalized travel costs from a multi-layer perspective. *Reliability Engineering & System Safety* 264, 111375.
- Wang, E., Ren, H., Hong, C., et al., 2021b. Cascading failures in coupled map lattices with sustained attack. *International Journal of Modern Physics C* 32 (9), 2150126.
- Wang, B., Su, Q., Chin, K.S., 2021a. Vulnerability assessment of China–Europe railway express multimodal transport network under cascading failures. *Physica A: Statistical Mechanics and its Applications* 584, 126359.
- Wang, Y., Tian, C., 2020. Measure vulnerability of metro network under cascading failure. *IEEE Access* 9, 683–692.
- Wang, J., Wang, S., Wang, Z., 2022. Robustness of spontaneous cascading dynamics driven by reachable area. *Physica A: Statistical Mechanics and its Applications* 585, 126399.
- Wang, N., Wu, M., Yuen, K.F., 2023b. A novel method to assess urban multimodal transportation system resilience considering passenger demand and infrastructure supply. *Reliability Engineering & System Safety* 238, 109478.
- Wang, L., Zhang, S., Szűcs, G., et al., 2024c. Identifying the critical nodes in multi-modal transportation network with a traffic demand-based computational method. *Reliability Engineering & System Safety* 244, 109956.
- Wang, Y., Zhou, Y., Yang, H., et al., 2023c. Integrated optimization of bus bridging service design and passenger assignment in response to urban rail transit disruptions. *Transportation Research Part C: Emerging Technologies* 150, 104098.
- Watts, D.J., 2002. A simple model of global cascades on random networks. *Proceedings of the National Academy of Sciences of the United States of America* 99, 5766–5771.
- Watts, D.J., Strogatz, S.H., 1998. Collective dynamics of “small-world” networks. *Nature* 393, 440–442.
- Wu, Y., Chen, Z., Zhao, X., et al., 2021b. Robust analysis of cascading failures in complex networks. *Physica A: Statistical Mechanics and its Applications* 583, 126320.
- Wu, S., Zhu, Y., Li, N., et al., 2021a. Urban rail transit system network reliability analysis based on a coupled map lattice model. *Journal of Advanced Transportation* 2021 (1), 5548956.
- Xiao, X., Jia, L., Wang, Y., 2018. Correlation between heterogeneity and vulnerability of subway networks based on passenger flow. *Journal of Rail Transport Planning & Management* 8 (2), 145–157.
- Xiao, Y., Li, Y., Liu, W., et al., 2025. Resilience assessment of high-speed railway networks from the spatio-temporal perspective: a case study in Jiangsu Province, China. *Reliability Engineering & System Safety* 259, 110900.
- Xiao, Y., Ren, Y., 2024. Application of K-Shell algorithm in key point identification and cascading failure in urban public safety transportation network. *IEEE Access* 12, 32152–32163.
- Xing, R., Yang, Q., Zheng, L., 2018. Research on cascading failure model of urban regional traffic network under random attacks. *Discrete Dynamics in Nature and Society* 2018 (1), 1915695.
- Xiong, Z., Yao, Z., 2020. Influence scope of cascading failure on rail transit system. *Journal of Transportation Systems Engineering & Information Technology* 20 (1), 12–18.
- Xu, Z., Chen, Z., Liu, X., 2025. Resilience analysis of bike-bus-metro multimodal transit network: case study in Chengdu, China. *Journal of Transport Geography* 128, 104338.
- Xu, J., Huang, H., Cheng, Y., et al., 2022. Vulnerability assessment of freeway network considering the probabilities and consequences from a perspective based on network cascade failure. *PloS ONE* 17 (3), e0265260.
- Xu, Y., Wandelt, S., Sun, X., 2023b. IMMUNER: integrated multimodal mobility under network disruptions. *IEEE Transactions on Intelligent Transportation Systems* 24 (2), 1480–1494.
- Xu, M., Wu, J., Liu, M., et al., 2018. Discovery of critical nodes in road networks through mining from vehicle trajectories. *IEEE Transactions on Intelligent Transportation Systems* 20 (2), 583–593.
- Xu, Z., Zhang, C., Chopra, S., 2023a. Robustness assessment of public bus transit system with a response-integrated approach for a resilient public transport system in Hong Kong. *Transportmetrica B: Transport Dynamics* 11 (1), 361–375.
- Yang, Z., Dong, X., Guo, L., 2023. Scenario inference model of urban metro system cascading failure under extreme rainfall conditions. *Reliability Engineering & System Safety* 229, 108888.
- Yang, Y., Huang, H., Li, G., et al., 2025a. A systematic review of resilience assessment and enhancement of urban integrated

- transportation networks. *Journal of Transport Geography* 129, 104420.
- Yang, Z., Liu, X., Wang, J., et al., 2025b. Assessment on resilience of urban agglomeration transportation system considering passenger choice and load-capacity factor. *Reliability Engineering & System Safety* 253, 110527.
- Yang, Y., Liu, Y., Zhou, M., et al., 2015. Robustness assessment of urban rail transit based on complex network theory: a case study of the Beijing Subway. *Safety Science* 79, 149–162.
- Ye, H., Luo, X., 2021. Cascading failure analysis on Shanghai metro networks: an improved coupled map lattices model based on graph attention networks. *International Journal of Environmental Research and Public Health* 19 (1), 204.
- Ye, Y., Wen, H., Zhang, L., et al., 2025. A multi-factor integrated vulnerability assessment framework for multi-layer intercity road networks considering cross-layer path selection. *Physica A: Statistical Mechanics and its Applications* 675, 130807.
- Yin, D., Huang, W., Shuai, B., et al., 2022. Structural characteristics analysis and cascading failure impact analysis of urban rail transit network: from the perspective of multi-layer network. *Reliability Engineering & System Safety* 218, 108161.
- Yin, R., Song, X., 2023. Mitigation strategy of cascading failures in urban traffic congestion based on complex networks. *International Journal of Modern Physics C* 34 (2), 2350022.
- Yin, R., Yuan, H., Wang, J., et al., 2021. Modeling and analyzing cascading dynamics of the urban road traffic network. *Physica A: Statistical Mechanics and its Applications* 566, 125600.
- Yussif, A.-M., Taiwo, R., Zayed, T., 2025. Enhancing sustainable urban mobility: computer vision applications in pedestrian path studies. *Journal of Traffic and Transportation Engineering (English Edition)* 12 (5), 1415–1451.
- Zargiannaki, E., Tzouras, P.G., Antoniou, E., et al., 2024. Assessing the impacts of traffic calming at network level: a multimodal agent-based simulation. *Journal of Traffic and Transportation Engineering (English Edition)* 11 (1), 41–54.
- Zeng, M., Cheng, Z., Lei, J., 2025. Carbon-optimization driven resilience assessment of cascading failure for multimodal transportation networks within the belt and road initiative. *Journal of Cleaner Production* 521, 146200.
- Zhang, L., Fu, B., Li, Y., 2016. Cascading failure of urban weighted public transit network under single station happening emergency. *Procedia Engineering* 137, 259–266.
- Zhang, N., Graham, D.J., Hörcher, D., et al., 2021b. A causal inference approach to measure the vulnerability of urban metro systems. *Transportation* 48 (6), 3269–3300.
- Zhang, M., Huang, T., Guo, Z., et al., 2022a. Complex-network-based traffic network analysis and dynamics: a comprehensive review. *Physica A: Statistical Mechanics and its Applications* 607, 128063.
- Zhang, Z., Li, X., Li, H., 2015b. A quantitative approach for assessing the critical nodal and linear elements of a railway infrastructure. *International Journal of Critical Infrastructure Protection* 8, 3–15.
- Zhang, S., Lo, H.K., 2018. Metro disruption management: optimal initiation time of substitute bus services under uncertain system recovery time. *Transportation Research Part C: Emerging Technologies* 97, 409–427.
- Zhang, L., Lu, J., Fu, B., et al., 2018. A review and prospect for the complexity and resilience of urban public transit network based on complex network theory. *Complexity* 2018 (1), 2156309.
- Zhang, L., Lu, J., Fu, B., et al., 2019a. A quantitatively controllable mesoscopic reliability model of an interdependent public transit network considering congestion, time-delay interaction and self-organization effects. *Nonlinear Dynamics* 96 (3), 933–958.
- Zhang, L., Lu, J., Fu, B., et al., 2019b. A cascading failures model of weighted bus transit route network under route failure perspective considering link prediction effect. *Physica A: Statistical Mechanics and its Applications* 523, 1315–1330.
- Zhang, Y., Lu, Y., Lu, G., et al., 2015a. Analysis of road traffic network cascade failures with coupled map lattice method. *Mathematical Problems in Engineering* 2015 (1), 101059.
- Zhang, J., Min, Q., Zhou, Y., et al., 2024a. Vulnerability assessments of urban rail transit networks based on extended coupled map lattices with evacuation capability. *Reliability Engineering & System Safety* 243, 109826.
- Zhang, Y., Ng, S.T., 2022. Robustness of urban railway networks against the cascading failures induced by the fluctuation of passenger flow. *Reliability Engineering & System Safety* 219, 108227.
- Zhang, H., Song, G., He, F., et al., 2024b. Dynamic evaluation method for urban road network resilience based on congestion propagation and dissipation. *Transportation Research Record* 2678, 75–89.
- Zhang, J., Wang, Z., Wang, S., et al., 2021a. Vulnerability assessments of weighted urban rail transit networks with integrated coupled map lattices. *Reliability Engineering & System Safety* 214, 107707.
- Zhang, L., Wen, H., Lu, J., et al., 2022b. Exploring cascading reliability of multi-modal public transit network based on complex networks. *Reliability Engineering & System Safety* 221, 108367.
- Zhang, L., Xu, M., Wang, S., 2023. Quantifying bus route service disruptions under interdependent cascading failures of a multimodal public transit system based on an improved coupled map lattice model. *Reliability Engineering & System Safety* 235, 109250.
- Zhang, L., Xu, M., Wang, S., 2024c. Improving robustness of large-scale bus transit networks against cascading failures: a preventive control or an emergency control? *Transportation Research Part C: Emerging Technologies* 162, 104602.
- Zhang, L., Xu, M., Wang, S., 2024d. Mitigating vulnerability of a multimodal public transit system for sustainable megacities: a real-time operational control method. *Sustainable Cities and Society* 101, 105142.
- Zheng, S., Chen, Y., Zhou, Y., et al., 2023. Influence of link-addition strategies on network balance and passenger experience in rail networks. *Sustainable Cities and Society* 91, 104415.
- Zhong, Q., Liu, S., Guo, J., et al., 2024. Restoration model for cascading overload failure in syncretic railway network. *Journal of Advanced Transportation* 2024 (1), 8244319.
- Zhou, W., Li, T., Ding, R., et al., 2023. Analysis of the influence and propagation law of urban rail transit disruptions: a case study of Beijing rail transit. *Applied Sciences* 13 (14), 8040.
- Zhou, Y., Wang, J., 2017. Critical link analysis for urban transportation systems. *IEEE Transactions on Intelligent Transportation Systems* 19 (2), 402–415.
- Zhou, Y., Zhang, M., Deng, S., et al., 2025. Node importance calculation in bus-metro composite network considering land use. *Tunnelling and Underground Space Technology* 163, 106723.
- Zhu, C., Tang, Z., An, C., et al., 2024. Research on chaotic characteristics of cascade failure in rail transit networks considering nonlinear load fluctuations. *Journal of Advanced Transportation* 2024 (1), 9093078.
- Zhu, T., Yang, X., Ma, Z., et al., 2025. Can a bottleneck capacity enhancement policy postpone infrastructure network collapse? *Transport Policy* 163, 1–13.



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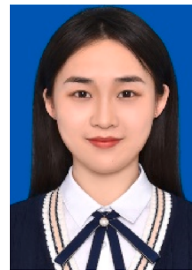
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